DELIVERY TIME VARIANCE REDUCTION
IN THE MILITARY SUPPLY CHAIN

THESIS

Preston L. Goodrich, Second Lieutenant, USAF

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DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

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Preston L. Goodrich, BS

Second Lieutenant, USAF

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Preston L. Goodrich, BS
Second Lieutenant, USAF

Approved:

____ ____________________

James T. Moore Ph.D. (Co-Advisor) date

____ ____________________

August G. Roesener, Ph.D. (Co-Advisor) date

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Abstract

The United States Transportation Command (USTRANSCOM) is currently responsible for the daily shipment of supplies to forward operating bases throughout Afghanistan. Aerial cargo shipments are an important method used to quickly deliver items that are needed immediately. Currently, delivery times vary greatly. This variation causes a decrease in confidence for on-time deliveries. As a result, shipments are demanded early and often, causing bottlenecks in the transportation system and fewer on-time deliveries. This paper analyzes data gathered through the global transportation network to determine shipment characteristics that cause the greatest amount of delivery time variance. A simulation is developed using the ARENA simulation software package that models cargo shipments into aerial ports in Afghanistan. Designed experiments and a simulation optimizer, OptQuest, are used to determine the most effective methods of reducing delivery time variance at individual aerial ports in Afghanistan as well as the system as a whole. The results indicate that adjustments in port hold times can decrease the overall delivery time variance in the system.

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To My Wife and Family

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DELIVERY TIME VARIANCE REDUCTION IN THE MILITARY SUPPLY CHAIN

I. Introduction

Background

Military operations conducted by the United States (U.S.) in Afghanistan, Iraq and other locations around the world currently require the defense logistic system to transport thousands of cargo pallets every month in support of these efforts. Without the timely and efficient delivery of this cargo, commanders and troops may not have their required equipment and are therefore less effective in accomplishing their missions. The United States Transportation Command (USTRANSCOM) owns and operates the defense logistic system. During the last several years, many different initiatives have addressed the optimization of the cargo delivery system. Most of these initiatives focus on minimizing the average delivery time of pallets through the optimization of the entire system or sub optimization of individual components of the system. While extremely worthwhile endeavors, these efforts do not consider the overall variance in the system; a decrease in the average delivery time accompanied by a relatively large increase in the variance of delivery times does not necessarily improve the system. Prior to further explaining the problem under consideration in this research, it is necessary to describe USTRANSCOM, its aerial component, Air Mobility Command (AMC), and the Global Transportation Network (GTN).

US Transportation Command and Air Mobility Command

After the terrorist attacks on the World Trade Center and Pentagon on September 11, 2001, it became evident that a rapid and agile distribution system was required. For the Department of Defense (DoD), this distribution process begins with acquisition and does not end until the war fighter receives their equipment. Obviously, numerous organizations and structures exist through which equipment must pass before reaching its designated location. Unfortunately, but understandably, many of these organizations are operated independently from one another and answer to independent and different chains of command.

In order to mitigate this problem, a single organization was put in charge of overseeing the entire process. In September 2003, the Secretary of Defense, Donald Rumsfeld, designated "U.S. Transportation Command as the single Department of Defense Distribution Process Owner (DPO)" (USTRANSCOM, 2004). Although USTRANSCOM does not currently own all processes involved in the distribution system, their span of influence does extend across all organizations involved.

In order to fulfill their duties as DPO, USTRANSCOM coordinates with numerous national partners to plan and execute its mission effectively. USTRANSCOM is the single entity in charge of directing and supervising the strategic distribution system. Current national DPO partners are:

> "the Defense Logistics Agency (DLA), US Joint Forces Command (USJFCOM), the Joint Staff Logistics Directorate (JS J-4), Under Secretary of Defense for Acquisition, Technology and Logistics (USD(AT&L)), Deputy Undersecretary of Defense for Logistics and Materiel Readiness (DUSD(L&MR)) and the various Service logistics commands, as well as USTRANSCOM's three component commands—Military Surface Deployment and Distribution Command (SDDC),

> Military Sealift Command (MSC), and Air Mobility Command (AMC)" (US Transportation Command Public Affairs, June 2006).

According to the USTRANSCOM website, during an average week more than 1,900 air missions are conducted, approximately 25 ships are underway and 10,000 ground shipments are en route. These activities operate in more than 75 percent of the nations worldwide. As of October 2004, "the command has moved more than 1.9 million passengers; 1.1 million tons by air; 3.7 million tons by sea; and delivered more than 53.7 billion barrels of fuel by ship" (USTRANSCOM, 2009).

AMC, the airlift component of USTRANSCOM, enables the rapid deployment of troops anywhere in the world as well as the continual delivery of supplies to sustain them throughout their mission. The principle aircraft responsible for airlift are the C-5 Galaxy, KC-10 Extender, C-17 Globemaster III, C-130 Hercules and KC-135 Stratotanker. In addition to this fleet of aircraft, the Civil Reserve Air Fleet (CRAF) also assists with the daily operations of AMC. Selected aircraft from airlines throughout the United States are designated as CRAF. These aircraft are available to AMC when the military fleet is unable to meet the demand of the defense logistics system. The airlines in the CRAF program elect to guarantee a certain number of aircraft from their fleets to be available when necessary. In return for this guarantee, they are given primary access to bid on weekly cargo shipment contracts. As of May 2007, 37 carriers and 1,364 aircraft were enrolled in the CRAF program (USTRANSCOM, 2009).

Global Transportation Network

Every day in the DoD's transportation network, personnel, weapons, equipment and other cargo items are transported to hundreds of different locations around the world.

Alan Heath, a program manager for Lockheed Martin, indicated that one of the main problems revealed from post Gulf War analysis was "a lack of readily accessible information and visibility into the shipment process, and nagging doubts about on-time deliveries that led to repeat orders and overstocking of materiel" (Heath, 2002). He states that the ports of Saudi Arabia were filled with shipments that were unmarked and thus undelivered. The undelivered cargo was inevitably reordered which only added to the build up in the ports and frustration on the front lines. This led to the development of a web-based system known as the GTN. This system captures the movement of cargo and passengers electronically which enables users to track shipments and schedule deliveries more efficiently (Erwin, 2009).

Over the past two decades, readily accessible information about supplies and visibility into the supply chain has become increasingly important. This ability has become known as in-transit visibility (ITV). ITV enables the customers, operators, owners, etc. of a supply chain to access current information on the location of cargo throughout the transportation process. It allows users to know the exact location of all shipments and more accurately determine expected delivery times. It also allows them to measure throughput and adjust the system as required to meet specific demands (Webber, 2006).

These insights have been made possible through advances in the technology used in the GTN. Automatic Identification (AID) is a technology that automatically senses and reports the location of cargo as it travels through the supply chain. This technology eliminates paper records and greatly reduces the amount of human interaction required to accurately track cargo. One of the most developed AID systems is commonly known as

Radio Frequency Identification (RFID). Alan Webber is a senior government analyst with Forrester research. In an article in the Defense Transportation Journal, he states that "the adoption of AID technologies like RFID is driven by the need for uninterrupted visibility of assets and inventory across a given supply chain" (Webber, 2006). This technology has advanced significantly over the last ten years due to heavy system employment by the DoD and the Wal-Mart chain of stores.

According to Webber, some of the current benefits of RFID applications used by numerous organizations include:

1. Improved efficiency and quality in production management,
2. Increased understanding of base business processes, and
3. Enhanced insight into the supply chain (Webber, 2006).

He also indicates that some of the areas that will see RFID and related sensor applications in the near future include:

1. Integration of information and physical security,
2. Ensuring application of the right asset to the problem, and
3. Visibility at all choke points in a business network (Webber 2006).

Currently, there are two main types of RFID technologies that are used in the DoD: passive and active RFID systems. For each type, a unique identification tag is attached to the cargo. For the passive system, these tags are read at each location by radio frequency (RF) readers with a range of less than 10 feet. The active readers systems are more complex and more expensive but have the advantage of being able to read tags from a distance of 300 feet indoors and 1000 feet outdoors (Cougher, 2006). The active RFID system does not need a human scanner to interact with the system and physically scan each item (similar to a cashier at a grocery store); instead the RF tags actively transmit their location to active RFID readers nearby.

According to Ed Coyle, a research fellow with LMI Government Consulting, "beyond tracking assets more precisely in the supply chain, the major benefit [that Automatic Identification] technologies bring lies within their power to capture data. Logistics professionals must learn how to leverage the power of this data by processing it and distilling it into manageable parts" (Coyle, 2006). Much of the data in the GTN is gathered by means of RFID technology. It is then processed and refined in such a way that allows users to easily access the information or transform it for their own use.

According to the USTRANSCOM, "GTN gives its customers located anywhere in the world a seamless, near-real-time capability to access and employ transportation and deployment information" (Global Transportation Network, 2009). This near-real-time access to information is able to reduce the number of lost, undelivered and reordered cargo by boosting the confidence of those employing the defense transportation process. The amount of data collected by the GTN quickly grows to a size that is impossible to analyze without proper computing tools.

The GTN is a fully automated command and control information system. The system is able to collect information from numerous different transportation systems and integrate it into a single information system (Global Transportation Network, 2009). Air, land and sea operations are integrated in a single data system. The Global Air Transportation and Execution System (GATES) is AMC's information system that reports air operations ITV data to the GTN. This information is then available for ITV, command and control, business operations and other applications that may benefit from the data.

Problem Statement

A reduction in delivery time variance will, in the long run, lead to a more reliable system through increasing the number of on-time deliveries, increasing potential throughput and decreasing average delivery time. Although many efforts have been undertaken to minimize the average delivery time of pallets through both global and local optimization techniques, the delivery time variance of cargo pallets frequently is either overlooked or in some cases amplified by these techniques. In some cases, the local optimization of a particular process has caused an overall increase in average cargo delivery time across the entire GTN. A local optimization can cause backups at airports, over utilization of manpower and inefficient consumption of resources. A global optimization should reduce the average cargo delivery time for the entire process but could also result in higher variance in cargo delivery times.

The variance in cargo delivery times causes equipment and supplies to be ordered often and as early as possible. A more consistent system will build confidence in the supported personnel which will allow them to order only what is needed in the near future and receive it when needed. For example, if a unit requires a certain set of supplies in the near future, and they know the average delivery time for these supplies is seven days but could require as much as 25 days for delivery, the unit will probably order the supplies 25 days ahead of time. On the other hand, if the average delivery time is 10 days and the longest possible delivery time is 14 days, unit personnel will likely only order the supplies two weeks before they are required. In these situations, the personnel plan for the worst case delivery time to ensure they have the required equipment when needed. Delivery time variance reduction will not necessarily result in the minimization of the average cargo delivery time, but will enable more on-time deliveries, higher potential throughput and a lower average cargo delivery time in comparison to historical values.

The aerial component of the GTN consists of *aerial ports* (AP), aircraft flight segments and cargo. In a network representation of the GTN, the APs are indicated by nodes of the network while the aircraft flight segments are the arcs. The node at which a pallet begins a segment is called the *aerial port of embarkation* (APOE) and the node at which a pallet ends a particular segment is called the *aerial port of debarkation* (APOD). Cargo is palletized at various APs, many of which are located within the United States. The AP at which a pallet is created is called the *pallet APOE*. The *pallet APOD* is the pallet's final destination. A combination of flight segments that begins at a pallet APOE and ends at a pallet APOD is called a *channel route*. Intermediary APs in a pallet's routing through the network are called *transload hubs*. At a transload hub, the pallet is unloaded from the arriving aircraft and then reloaded (possibly after a delay on the ground) onto another aircraft and routed to the next AP or APOD. The amount of time a pallet is on the ground at a transload hub is called the *transload time*. The emphasis of this research is to identify those transload hubs at which reductions in transload time variance is of greatest value.

Research Objectives and Questions

This research uses cargo delivery data from January 2008 to May 2009 provided by AMC to accomplish two objectives. First, the data is used to analyze theater transportation activity and identify those areas that are the source of above average variance. Second, the data is used in conjunction with a simulation to determine which approaches would provide the greatest reduction in delivery time variance throughout the system.

The overall variance in cargo delivery time in the system is viewed as a function of the variance of individual processes within the system. In order to reduce the overall variance, individual areas with high variance are identified. The transload hubs are the first processes to be considered. Aircraft and mission types are also analyzed to determine if these subcategories exhibit above average variance.

A simulation model was developed to model the overall defense logistics system moving cargo into Afghanistan. A designed experiment limited the simulation inputs and aided in identifying those aspects of the defense logistics system which can be modified to efficiently reduce the overall variance of system delivery time.

Methodology

The methodology for this research can be broken down into three distinct steps. First, the scope of the problem is defined and the data is reduced accordingly. Second, the available data is explored and analyzed in order to determine sources of variance throughout the system, such as the type of aircraft which transported the pallet, the pallet size and weight and locations at which the pallet was transloaded. Statistical tests are used to differentiate between delivery time variance for the different cargo pallet characteristics. Finally, a simulation model was developed and a designed experiment utilized to determine those areas that would most effectively reduce variance across the system.

Limitations

This project assumes that the GATES data provided is both accurate and complete. Since the GATES data is used to model the air component of the GTN by deriving flow of cargo and fitting distributions according to the data, it is assumed that it accurately reflects field operations. Furthermore this project utilizes distributions of transload times to model the amount of time a pallet remains on the ground between aerial movements en route to its final destination. The project also utilizes distributions to model transportation times between APs. These distributions do not necessarily capture all relevant interactions between resources and demand in the system accurately.

Summary

Increases in ITV and data sources such as GTN and GATES provide volumes of information that can be utilized to analyze the cargo transportation system. Delivery time variance reduction throughout the system would increase reliability in the system and ensure more on-time deliveries. This research targets transload hubs in an effort to reduce delivery time variance.

Prior to detailing this research endeavor, it is necessary to present a brief review of recent literature involving this particular problem, including a description of the military airlift system and a review of AMC's modeling and statistical testing; this information is given in Chapter II. The literature review is followed by Chapter III in which a more rigorous description of the problem as well as an explanation of the methodologies and techniques used throughout this research is provided. Next, a detailed description of the results and analysis of this research endeavor is presented in Chapter

IV. This research effort ends with a discussion of the conclusions learned throughout the research process as well as recommendations for future research areas in Chapter V.

II. Literature Review

The Corrupting Influence of Variance

Many modern supply chain management theories indicate that system variance reduction should be one of the primary steps considered to increase the overall system performance (Hopp & Spearman,1996; Sabri and Beamon, 2000; Guiffrida and Nagi, 2006). Wallace J. Hopp and Mark L. Spearman co-authored *Factory Physics: Foundations of Manufacturing Management* (1996). An interesting chapter in this book is entitled "The Corrupting Influence of Variability." Although the ideas presented in this book were originally applied within the theoretical confines of a manufacturing facility, they can be easily related to supply chain or transportation system management as shown throughout the remainder of this section.

There are two basic properties of networks that enable the corrupting influence of variability: flow conservation and capacity limits. Flow conservation can be simply defined as the requirement that the incoming flow must equal the outgoing flow or the net flow of a system must be zero. Hopp and Spearman argue that "in a stable system, over the long run, the rate out of a workstation will equal the rate in, less any yield loss, plus any parts production within the workstation" (Hopp and Spearman, 1996). In a transportation network, all cargo and passengers that enter the system must necessarily exit the system at some point; thus flow conservation is maintained whether the cargo and passengers exit at the designated point or are damaged or diverted while en route. Capacity limits, in contrast, can be defined in terms of arrival and processing rates. In order for a system to stabilize, it is necessary for the arrival rate to be strictly less than the processing rate. If a process is in steady state, "all plants will release work at an average rate that is strictly less than the average capacity" (Hopp and Spearman, 1996).

Two of the most obvious and important manifestations of variability in a transportation system are arrival rates and processing rates. These measures are defined by mean, μ, and variance, σ^2, respectively. The arrival rate quantifies how quickly orders enter the system; therefore, when demand for cargo increases, the arrival rate also increases. The processing rate quantifies how quickly a shipment is moved to the next processing center or how quickly shipments move from port to port.

Regardless of source, variation in a system will inevitably cause increases in average delivery times. Furthermore, variation which occurs earlier in a process causes greater increase in average delivery time than the same variation later in the process (Hopp and Spearman, 1996). Hopp and Spearman (1996) illustrate this theory through an example in which one of two machines in series configuration is to be replaced by a third machine with a lower process time variation. If the second machine is replaced, the process time variation for that machine is reduced and the overall variation in the system is reduced. On the other hand, if the first machine is replaced, the process time variation for that machine is reduced and the variance reduction from the first machine decreases the variance in arrivals for the second machine, thereby further reducing the total variance in the system and reducing mean processing time as well. Therefore, it is most important to address issues of variability earlier in a system as long as it is financially beneficial to do so. By reducing variability early in a system, the variance in arrival times at subsequent stations is reduced. Reductions in variance at the beginning of a system impact efficiency at all subsequent stations, whereas variance reduction at the end of a system only impacts efficiency at the final station.

Optimal Variance Structures

As noted in the previous section, variability in a system causes inefficiencies. In a transportation network, these inefficiencies can cause undesirable delivery times, lower throughput and reduced productivity. At the same time, reducing the variability throughout a system requires the expenditure of potentially scarce resources. For this reason, the process of reducing variability must also be achieved with care. A dollar spent on variability reduction in one area is a dollar that cannot be spent on variability reduction in another area or elsewhere. Therefore, a plan must be devised that utilizes all resources in an effective manner.

A number of different studies have been conducted regarding the optimal use of resources in variability reduction. Using a deterministic branch and bound technique, Erlebacher and Singh (1999) concluded that there are two desirable variance structures for processing times on synchronous or paced assembly lines. The two desirable variance structures are a uniform configuration where the variance is evenly distributed among the different stations and a spike-shaped configuration where the majority of the variance is concentrated at one station and the other stations have relatively little variance in processing times. They also showed that the spike-shaped configuration is more desirable if the total variance throughout the entire system exceeds a critical level even after variance reduction has been performed; otherwise, the uniform configuration is more desirable (Erlebacher and Singh, 1999).

In another study, Lau (1992) presents results gained through a simulation study of an asynchronous or unpaced assembly line. Lau identified three desirable variability reduction structures: bowl, symmetry and spike. The bowl structure concentrates the majority of the variance in the stations that are near the beginning and end; the lowest variance stations are at the midpoint of the process. A bowl shape emerges by graphing the variability for each station (Lau, 1992). The symmetry structure is similar to that of Erlebacher's and Singh's uniform structure. The spike structures in both studies are interchangeable.

Economics of Variance Reduction

Beyond the idea of expendable resource availability for improving the transportation system or supply chain performance is the concept of variability reduction economics. Guiffrida and Nagi (2006) investigate the effects of variability reduction within a system. They argue that the financial justification of investment in delivery time improvement can be benchmarked against the expected penalty cost of an untimely delivery. If the present worth of the expected penalty cost over a defined time horizon is greater than or equal to the cost of improving the system, they should be willing to undertake the process improvement. In many cases, the penalty cost associated with untimely delivery is the opportunity cost of lost production. The authors note several instances of automotive manufacturers that fine suppliers for untimely deliveries. For example "Saturn levies fines of $500 per minute against suppliers who cause production line stoppages" (Guiffrida & Nagi, 2006). In these cases, the penalty cost is defined by the customer.

Air Mobility Transportation Modeling

AMC is responsible for the efficient assignment of aircraft, crews and resources to meet demand for airlift missions throughout the DoD. The optimization of these resources is a complex problem that is further complicated by continual changes in the problem parameters. An efficient solution to the airlift needs must be found and then adapted to the continually changing constraints and requirements. Years of research and resources have been applied to the many different aspects of this problem in order to reduce costs and improve the efficiency of the system. The following paragraphs present an overview of some of the methods recently used to optimize the military airlift system.

Strategic Mobility Models

McKinzie and Barnes (2004) offer a comprehensive review of models currently used to address strategic mobility. These models are designed to represent and analyze the flow of cargo and passengers into theater. According to the authors, the four major strategic mobility models in use today are Global Deployment Analysis System (GDAS), Joint Flow and Analysis System for Transportation (JFAST), Model for Intertheater Deployment by Air and Sea (MIDAS), and Mobility Simulation Model (MobSim).

GDAS is used to analyze transportation policy issues and operational planning tasks for large or small scale force deployments. It allows users to model new technologies and define new ports and capabilities before they exist to determine their value.

JFAST is used to forecast transportation requirements, perform course of action analysis, evaluate "what-if" scenarios and build delivery profiles of troops and equipment. It routes all types of transportation modes through a network to identify bottlenecks, determine lift requirements and project force closures.

MIDAS is used to measure the capability of a given set of strategic transportation assets to deploy a specified force. It is also used to project a schedule for a deployment, determine modes of transportation and adapt scenarios to unexpected events.

MobSim is a discrete event simulation capable of modeling many different modes of transportation for passengers and cargo moving across the network. It is capable of modeling aircrew scheduling and tanker refueling operations.

Overall, the models can be grouped into two main categories. GDAS and MIDAS are generally used for resource planning while JFAST and MobSim are used for deliberate planning. One major drawback to these models, according to the authors, is that they each lack advanced optimization techniques. In most cases, they use simplistic optimization algorithms or greedy approaches to optimize the scenarios (McKinzie and Barnes 2004).

Continuous Planning

Transportation problem planning and scheduling tools are typically designed to incorporate all constraints into the model and find an optimal solution. If a new constraint or requirement is added, the entire process is repeated. While this solution method may be useful for long-term planning or within a stable environment, it can lead to severe problems in a continually changing environment. One of the most apparent problems is the disparity from solution to solution. At times, a small change in problem formulation can lead to relatively large changes in the optimal solution. If solutions vary greatly, the schedule can become unstable and ultimately of no value. Another obvious problem with this solution method is the computational effort required to solve each problem instance from scratch. If updates to the system are presented several times a day, the algorithm will be continually re-optimizing the solution.

Smith et al. (2004) cite three items that distinguish the AMC resource management problem. First, it is a very complex problem due to the number of aircraft and aircrews that must be scheduled and the resulting resource availability and usage constraints. Second, the problem is further complicated because of the continuous planning and execution environment in which it exists. Third, the problem is distinguished by the need for flexible accommodation of and integration with human decision-making. In other words, the process must be flexible enough that users can override or guide decision making in particular cases. The article also describes the AMC allocator, which facilitates effective allocation of resources while requiring limited current airlift schedule changes. It uses a constraint based search heuristic to incrementally improve the solution, thereby allowing users to minimize or at least localize schedule changes (Smith et al., 2004).

Network and Integer Programming models

Network and integer programming models have also been developed to schedule aircraft and aircrews for monthly channel route cargo missions. Manually constructing schedules for channel routes is time consuming and unlikely to generate an optimal or near optimal solution. Network modeling and integer programming solution techniques allow optimal or near optimal solutions to be generated as a starting point for the monthly channel route cargo schedule. They can also develop multiple optimal or near optimal solutions to be considered by a decision maker, allowing them to tailor schedules to their priorities. Nielson et al. (2004) developed a mixed-integer network design formulation for the channel route scheduling problem as well as a pure integer program using a variable redefinition approach known as composite variable modeling. They demonstrated the ability to quickly achieve near optimal results using the second formulation (Nielson et al., 2004). This model's value is its ability to achieve a more efficient solution than a manually generated schedule and allow schedulers to focus on analyzing the schedule rather than generating the schedule.

Another integer programming approach designed to support the air mobility network prevents disruptions in the system due to overcrowding of aerial ports. Every port can accommodate a maximum number of aircraft at any single time. This constraint is known as maximum on ground (MOG). If the original schedule is disrupted by weather, equipment failures or other unforeseen circumstance, the schedule may become infeasible due to MOG. Bertsimas and Patterson (1998) show that by optimally controlling the release of aircraft into a network or controlling the speed of the aircraft after it has entered the network, the impact or cost of congestion at airports can be greatly reduced. Koepke et al. (2006) extended Bertsimas and Patterson's integer program formulation for the commercial airline Multi-Airport Ground-Holding Problem to the USAF air mobility network. The integer programming formulation developed by Koepke et al. is able to quickly recommend courses of action to prevent a port from becoming oversaturated with aircraft (2006). The algorithm quickly identifies which aircraft on the ground should be delayed in order to prevent a MOG constraint from being violated.

In this chapter, recent literature pertaining to the problem under consideration has been presented, including a description of the military airlift system and some of the techniques AMC has previously used to model it. The subsequent chapter provides a description of current simulation tools available to model and analyze the military airlift problem. A description of the methodology utilized in this study to better understand the military airlift system and investigate possible options to enhance its performance is also presented.

III. Methodology

The methodology for this research can be broken down into three distinct steps. First, the scope of the problem is defined and the data is reduced accordingly. Second, the available data is explored and analyzed in order to determine sources of variance such as aircraft type, pallet size and transload locations. Statistical tests are used to differentiate between delivery time variance for the different cargo pallet characteristics. Finally, a simulation model is developed and utilized to determine those areas that would most effectively reduce variance across the system.

Database Description

The data used for this analysis came from the Global Air Transportation and Execution System (GATES). This system is capable of processing and tracking all passenger and cargo transportation through aerial ports. The database used in this analysis contains a data entry for every pallet movement that occurs or every time a pallet is loaded and unloaded from an aircraft.

Table 1 shows the different columns of data used in this research. The data columns have been split to be more easily shown in this format. In the GATES database, shown in Table 1, each pallet is identified by a six character string in the field "PAL_ID." The first three characters identify the location from which the pallet originated. The next three characters uniquely distinguish the pallet from all other pallets with the same location of origination. The next field, "PAL_DT," gives the date and time at which the pallet was created.

Table 1: GATES Data Example

PLT_ID	PLT_DT	DEP_DT_TM	MDS	TAIL_NUM	ARR_DT_TM	APOE_APC	APOD_APC
KEZQDT	1/1/2008	1/4/2008	C017A	60002	1/4/2008	KEZ	OA1
KEZQDZ	1/1/2008	1/4/2008	C017A	60002	1/4/2008	KEZ	OA1
KEZQEB	1/1/2008	1/4/2008	C017A	60002	1/4/2008	KEZ	OA1
KEZQEC	1/1/2008	1/3/2008	C017A	44131	1/3/2008	KEZ	OA1

APOE_ICAO	APOD_ICAO	AIR_DIM_CD	PLT_APOE	PLT_APOD	PLT_VOL	PLT_HT	PLT_NET_WT
OKAS	OAIX	D	KEZ	OA1	215	39	6500
OKAS	OAIX	D	KEZ	OA1	259	47	6010
OKAS	OAIX	D	KEZ	OA1	259	47	6010
OKAS	OAIX	D	KEZ	OA1	259	47	6220

Each entry also includes the pallet aerial port of embarkation “PAL_APOE” and the pallet aerial port of debarkation “PAL_APOD.” These two fields contain a three letter designation known as an Airport Code (APC). This designation uniquely identifies each airport throughout the world. Most of the three letter designations are equivalent to a commonly used international coding system known as the International Air Transport Association (IATA) APC; however, some of the codes differ. Table 2 details codes used throughout this analysis.

Table 2: International Air Transport Association APC

APC	Location	APC	Location
CHS	Charleston AFB, SC	AZ1	Camp Bastion, Afghanistan
DOV	Dover AFB, DE	AZ3	Sharona Airstrip, Afghanistan
NGU	Norfolk, VA	JAA	Jalalabad, Afghanistan
WRI	McGuire AFB, PA	KBL	Kabul Intl, Afghanistan
RMS	Ramstein, Germany	KDH	Kandahar Intl., Afghanistan
ADA	Incirlik AB, Turkey	OA1	Bagram, Afghanistan
IUD	Al Udeid AB, Qatar	OA4	Salam, Afghanistan
FRU	Manas AB, Kyrgyzstan	KEZ	Ali Al Salem AB, Kuwait
KWI	Kuwait Intl., Kuwait		

Originally, the database contained entries for all pallet movements throughout the world from January 2008 to May 2009. To enable tractability of the problem, this data has been reduced to focus the analysis on Afghanistan and efforts being made to support Operation Enduring Freedom (OEF). This was accomplished by eliminating all entries that did not have a pallet aerial port of debarkation in Afghanistan. The data was also reduced by focusing on only the largest contributors to the support in Afghanistan. This includes the pallet aerial ports of embarkation of Charleston Air Force Base (AFB), Dover AFB, Norfolk Naval Station and McGuire AFB.

As previously mentioned, the database contains an entry for every pallet movement that occurs. The APOE and APOD are registered twice for each entry in the following fields respectively: "APOE_APC," "APOE_ICAO," "APOD_APC," and "APOD_ICAO." The APC identification is the same as mentioned in the previous paragraphs. The International Civil Aviation Organization (ICAO) APC is an internationally accepted four character designation that identifies all aerial ports throughout the world. A table of commonly used ICAO designations is presented in Table 3.

Table 3: International Civil Aviation Organization APC

ICAO	Location	ICAO	Location
KCHS	Charleston AFB, SC	OAZI	Camp Bastion, Afghanistan
KDOV	Dover AFB, DE	OASA	Sharona Airstrip, Afghanistan
KNGU	Norfolk, VA	OAJL	Jalalabad, Afghanistan
KWRI	McGuire AFB, PA	OAKB	Kabul Intl., Afghanistan
ETAR	Ramstein, Germany	OAKN	Kandahar Intl., Afghanistan
LTAG	Incirlik AB, Turkey	OAIX	Bagram, Afghanistan
OTBH	Al Udeid AB, Qatar	OASL	Salam, Afghanistan
UAFM	Manas AB, Kyrgyzstan	OKAS	Ali Al Salem AB, Kuwait
OKBK	Kuwait Intl., Kuwait		

In addition to the APOE and APOD information, GATES provides a time stamp. As each pallet is loaded or unloaded, the date and time is registered in the database.

These time stamps enable the determination of transport time from the APOE to the APOD as well as the amount of time a pallet remains on the ground at a transload hub. In other words, if the pallet has not yet reached its final destination, the transload time for the pallet can be determined. Each entry also identifies the type of aircraft by which the pallet was transported. The pallets are transported by a mixture of both civilian and military aircraft with varying capabilities. Table 4 depicts the number of pallets transported by each of the different aircraft types from January 2008 through May 2009. A total of 57,298 pallets were loaded and offloaded during this time period en route to various destinations in Afghanistan.

Table 4: Transported Pallets

Aircraft	Pallets Transported	Relative Percent
C-130	1120	1.95%
C-17	20861	36.41%
C-5	3915	6.83%
KC-10	711	1.24%
AN-124	1845	3.22%
B-747	16916	29.52%
DC-10	3485	6.08%
MD-11	8445	14.74%

AMC uses a mixture of organic military aircraft including the C-5, C-17, C-130 and KC-10 as well as commercially contracted aircraft from the CRAF program including the B-747, AN-124 and MD-11. The aircraft type designation is located under the "MDS" field. The tail number for each aircraft, shown as "TAIL_NUM," is also available to track aircraft specific shipments. As shown in Table 4, commercial aircraft were responsible for more than half of the total cargo pallet movements during this time period.

Finally, the database contains pallet specific information for each entry. The term "PLT_VOL" details the total dimensional volume occupied by the pallet in square feet; "PLT_HT" gives the pallet height measured in inches; "PLT_NET_WT" details the net weight of the pallet in pounds. The term "AIR_DIM_CD" contains a single character designation that identifies and describes the type of pallet that is being transported. The pallets are categorized by a single letter ranging from A to Z. Table 5 details each of the possible type codes and lists the number of pallet movements with that characteristic. These codes are further explained in the next section.

Table 5: Pallet Types

Type Code	Description	Number
A	Non-unitized; rolling stock, skid, non-palletized	2709
B	Low profile pallet	6217
C	Containerized	36
D	463L for 727/707/DC8/DC9/L188	34
E	463L for 747 belly	13018
F	463L for DC10; upstairs	1246
G	463L for DC10; downstairs	10789
H	463L for L100/C130 ramp	2
I	Pre-packed ISO container	309
J	463L for C130; 6 aisle way	8
K	Half pallets	0
L	463L for C5/L100/C130/747; upstairs C141/C17	17621
M	C5 only; over 100 inches	326
N	KC10; except for P and Q	603
P	KC10; position 1	38
Q	KC10; rear five positions	408
R	C5; 14 aisle way-positions 1, 2, 35, 36	62
S	463L for C17 Logistics pallet train	2240
T	Throughput ALOC pallet	306
U	A300 pallet train	32
V	Stack of empty pallets	0
W	Pallet with lox cart	0
X	Pallet for DC-8 combination	19
Y	ADS pallet train	1275
Z	Break-bulk ALOC pallet	0

Cargo Designations

For the aircraft listed in Table 4, the available pallet positions can be filled by a number of different cargo options. This section describes in detail the pallet types listed in Table 5.

Type code A encompasses all pallets or cargo that are considered non-unitized, rolling stock, skid or non-palletized. This includes all cargo that cannot be stored in a traditional container or pallet. Many of these methods are discussed in the following paragraphs.

The 463L is the designation that refers to a standardized pallet compatible with all USAF aircraft. It has been in use since the 1960s, although it has been significantly improved over the years. The 463L is comprised of aluminum over a balsa wood core; it is 88 inches wide, 108 inches long and 2 ¼ inches tall and weighs 290 pounds without optional side and top nets. The maximum load per pallet is 10,000 lbs of evenly distributed weight. A rail or roller system is available in all military aircraft which allows the cargo to be easily loaded and unloaded (GlobalSecurity, 2009).

International Standardization Organization (ISO) containers are standardized containers that can be transported by truck, train, ship and aircraft. The ISO is responsible for standardizing the size of the containers that are often transported via ships or on railcars. This system facilitates the transportation of goods across the globe by eliminating the need to unpack and repack items for shipping when the mode of transportation is changed. The containers come in several sizes. The most common are 8' 6" tall, 8' wide and 20' or 40' long and are capable of transporting up to 66,139 lbs of cargo (ISO, 2009).

A pallet train is a set of pallets that are coupled together to form a "train." The largest train utilized converts six standard pallets into a single pallet train. These 44 foot trains can weigh as much as 60,000 lbs. By using trains, the on- and off-loading times can be significantly reduced; however, these are only used when a significant amount of cargo is bound for the same location (ISO, 2009).

A break-bulk Army Logistics Center (ALOC) pallet refers to any standard pallet such as the 463L that is loaded with several individual items fastened to the pallet. If not secured using a pallet, the items would have to be loaded individually instead of in bulk.

In addition to these pallet specifications, cargo items can be classified as oversize or outsize cargo. Oversize cargo is any single piece of cargo that exceeds the allowable dimensions of a 463L standardized pallet but is less than or equal to 1,090” long 117” wide and 105” tall. This type of cargo can still be transported aboard the C-5, C-17 and C-130. Outsize cargo is any single piece of cargo that exceeds at least one of the allowable dimensions outlined for oversize cargo (1,090” long, 117” wide, or 105” tall) and thus requires transport aboard a C-5 or C-17 (AFPAM 10-1403, 2003).

Aircraft Types

The missions analyzed in this research are accomplished through a mixture of AMC aircraft (known as “organic” aircraft) and commercial aircraft from the CRAF program. Each of these aircraft has different mission capabilities such as maximum flying range and cargo capacity. Figure 1 contains schematics depicting the pallet carrying capabilities of each of the aircraft.

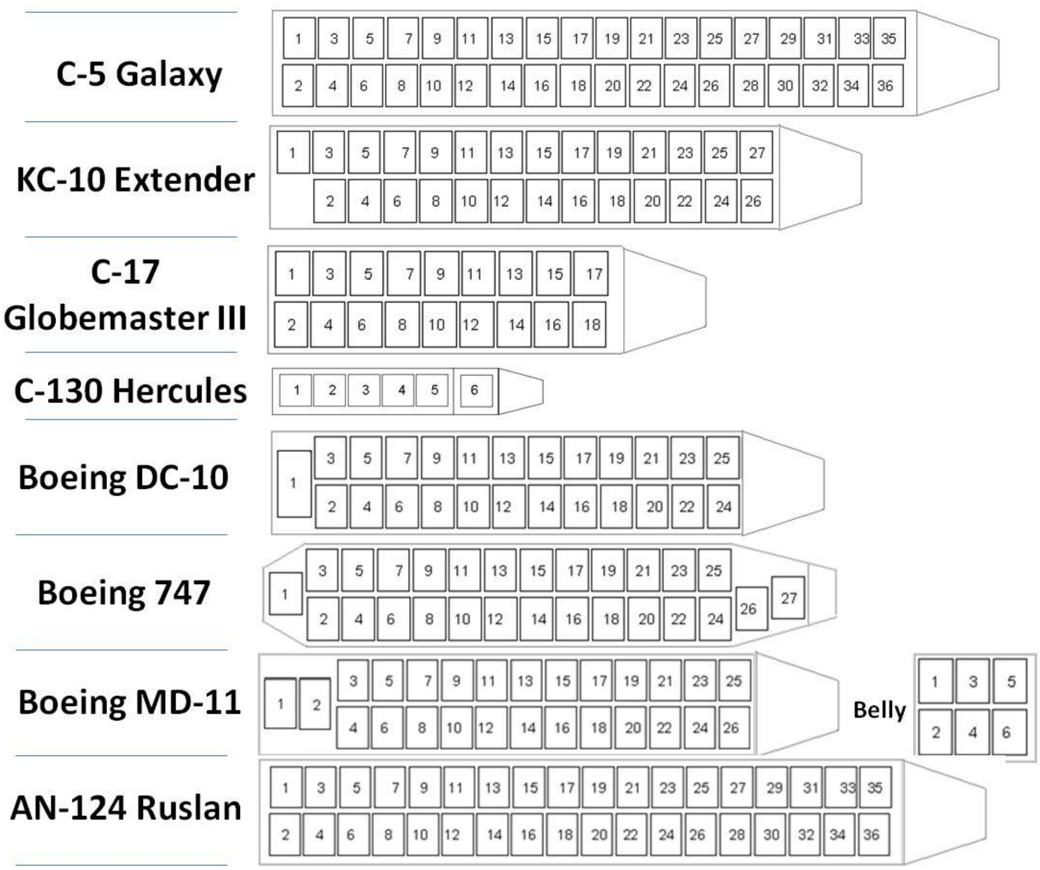


Figure 1: Aircraft Pallet Positions

To enhance understanding of the distribution process, a brief description of each aircraft's key features is presented in the following paragraphs.

The C-5 Galaxy is one of the largest aircraft in the world; it is the largest cargo aircraft in the United States Air Force (USAF) inventory. It is capable of carrying all of the Army's air-transportable combat equipment, to include bulky items such as the 74 ton Mobile Scissors Bridge. It has both forward and aft full size doors to facilitate rapid loading and unloading of cargo items. The landing gear is capable of lowering the parked aircraft to the height of a truck bed or help with the loading or unloading of vehicles. The cargo compartment is 13.5' tall, 19' wide and 143.75' long with a total of 36 pallet positions. It is capable of carrying 270,000 lbs 6,320 nautical miles without refueling and has an unlimited range using in flight refueling (USAF Factsheets, 2009).

The C-17 Globemaster III is the newest cargo aircraft in the USAF inventory, with the first production model delivered in 1993. The C-17 is an important asset because of its reliability and flexibility. It is capable of delivering troops and cargo to forward operating bases, performing tactical airlift and airdrop missions or being used for aero-medical evacuations. Furthermore, the aircraft is operated by a relatively small crew of three personnel (pilot, co-pilot and loadmaster). This aircraft is also capable of carrying almost all of the Army's air-transportable equipment that is loaded through a large aft door. The cargo compartment is 12' 4" tall, 18' wide and 88' long with 18 pallet positions. It is capable of carrying up to 170,900 lbs with a 2,400 nautical mile unrefueled range and unlimited in flight refueling range (USAF Factsheets, 2009).

The C-130 Hercules is primarily responsible for the tactical portion of the USAF airlift mission. These aircraft carry cargo from main operating bases to forward operating bases or other less developed or hostile areas. The cargo compartment for this aircraft is approximately 9' tall, 10' wide and 40' long. Although this aircraft is much smaller than the other cargo aircraft described in this section, it is able to accommodate a large variety of cargo including utility helicopters, armored vehicles, standardized pallet cargo and military personnel. When delivering cargo, the C-130 is capable of air dropping up to 42,000 lbs or landing on rough, dirt runways. The C-130H has a maximum range of 1,300 nautical miles, while the range of the upgraded C-130J is slightly further at 1,600 nautical miles. They can each be loaded with six pallets, 92 combat troops, or 64 paratroopers and have a maximum payload of 36,500 lbs (USAF Factsheets, 2009).

The KC-10 Extender is primarily considered to be an aerial refueling aircraft; however, it has the capacity to carry up to 170,000 lbs of cargo and as many as 75 military personnel. It often performs this function by refueling fighter aircraft while carrying the squadron's support personnel and equipment to an overseas deployment. With cargo, the KC-10 has a maximum range of 4,400 miles and a total of 27 pallet positions in the cargo compartment (USAF Factsheets, 2009).

The Boeing DC-10 is the commercial version of the USAF's KC-10 Extender. It is capable of carrying approximately 150,000 lbs of cargo up to 5,800 nautical miles. The cargo bay encompasses 16,000 square feet which can hold up to four 40 foot railroad freight cars or up to 380 passengers (Boeing, 2009).

The Boeing 747 is an easily recognizable passenger and cargo carrier that first flew commercially in 1970. There are currently several different models that vary in capabilities. The most commonly used model in this research is the 747-200. This model has a maximum range of 6,850 nautical miles and a maximum payload of 247,800 lbs (Boeing, 2009).

The Antonov 124 is a Ukrainian cargo carrier produced by Antonov Aeronautical Scientist/Technical Complex. Originally designed for strategic military airlift, it is now commonly used as an oversize cargo charter. Many of its features resemble those of the C-5 including forward and aft cargo doors and the capability to kneel or lower its cargo deck for easier loading and unloading. It has a maximum payload of 330,000 lbs and can accommodate up to 88 passengers on an upper deck (Antonov, 2009).

The Boeing MD-11 is a commercial aircraft available in models designed for freight, passengers or a combination of both. Depending on the configuration, the aircraft can carry 340,000 lbs of cargo or up to 400 passengers. At maximum takeoff weight, the MD-11 has an approximate range of 7,630 nautical miles. The aircraft first saw commercial service in 1990 and manufacturing of this model continued until 2001 (Boeing, 2009).

Each of these aircraft has unique characteristics that help AMC support the USAF and the DoD by delivering supplies, equipment and more on a daily basis. The following sections describe methods available to study and analyze the database that has been described.

Hypothesis Testing

Numerous methods have been devised to determine if the variances of two samples are statistically different; the two methods utilized by this research are the *f-test* and the *Kruskal-Wallis test*.

f-test

One of the functions of the *f-test* is to test for differences in variances among samples. The formula for the F-statistic is

$$F = \frac{s_1^2}{s_2^2}$$

where the variances (s_1^2 and s_2^2) are arranged so that $F > 1$. In other words, $s_1^2 > s_2^2$. The null and alternative hypotheses are then defined as:

$$H_0: s_1^2 = s_2^2$$

$$H_A: s_1^2 \neq s_2^2.$$

The alternative hypothesis, $H_A : s_1^2 > s_2^2$, may also be used to test that the variance s_1^2 is strictly greater than the variance s_2^2. Once the F-statistic has been calculated, the critical value can be determined from a table of F values present in most statistics text books (Wackerly et al., 2008). Many software programs also have tables to generate critical values. If the F-statistic is greater than the critical value, the null hypothesis is rejected in favor of the alternative hypothesis. Otherwise, there is insignificant evidence to reject the null hypothesis that the two samples have the same variance.

This procedure is based on the assumptions that the data are independently distributed and approximately normal. While the normality assumption is often ignored in comparison of sample means with little effect, the comparison of variances is often very sensitive to the non-normality assumption violation (Box 1953).

Kruskal-Wallis Test

The Kruskal-Wallis Test is designed to differentiate between different distributions that do not necessarily satisfy the assumption of normality. It is a non-parametric test that does not rely on any underlying distribution for validity. The null and alternative hypotheses for this test are

$H_0: The\ samples\ are\ from\ identical\ populations$

$H_A: At\ least\ one\ of\ the\ samples\ comes\ from\ a\ different\ population.$

To perform this test, the data is arranged in ascending order for all samples and a rank is assigned to each data point. In other words, the smallest value will receive a rank of 1, the second smallest will receive a rank of 2, etc. The test statistic

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1)$$

is calculated, where

$N = \sum n_i\ , the\ number\ of\ observations\ in\ all\ samples\ combined$

$n_i = the\ number\ of\ observations\ in\ the\ i^{th}\ sample$

$R_i = Sum\ of\ the\ ranks\ for\ sample\ i$

$k = number\ of\ samples$

The Kruskal-Wallis statistic is then distributed approximately chi-square with k - *1* degrees of freedom. If the calculated statistic is greater than the chi-square critical value, the null hypothesis will be rejected in favor of the alternative hypothesis. Otherwise, there is insignificant evidence to reject the null hypothesis that the samples come from the same population (Kruskal and Wallis, 1952).

Transformations

Another remedy for data which violates the normality assumptions involves transforming the data. Data transformations are capable of making the distribution of the sample data more closely resemble a normal distribution. The analysis can then continue with the transformed data set. There are many different types of transformations; some of the more commonly used transformations include the square root transformation, logarithmic transformation and inverse transformations. The square root transformation and the logarithmic transformation are most applicable to the data in this research.

The square root transformation computes the square root of each data entry. This transformation would be applicable and easy to implement because all data entries are positive; however, the data must be adjusted for the delivery times that take less than one day.

Logarithmic transformations are accomplished by taking the logarithm of each data entry. This can be performed for any logarithm base that is applicable to the data. The most common logarithmic transformations are the log_{10}, log_2 and log_e. The researcher may choose among all of these options to determine the transformation that best fits their needs. The assumptions of normality usually hold after a suitable transformation has been applied to the samples and allows for a traditional analysis to be accomplished (Box and Cox 1964).

Model Description

Prior to detailing the model developed in this research, it is necessary to describe the software used to develop the model.

ARENA

ARENA is a discrete event simulator produced by Rockwell Software. The software uses a graphical user interface that allows modelers to place modules in the workspace to represent different events or activities through which entities or objects of the model move and interact. The modules used to create the model used in this research include the *create*, *process*, *route*, *station*, *assign*, *decide*, *record* and *dispose* modules shown in Figure 2.

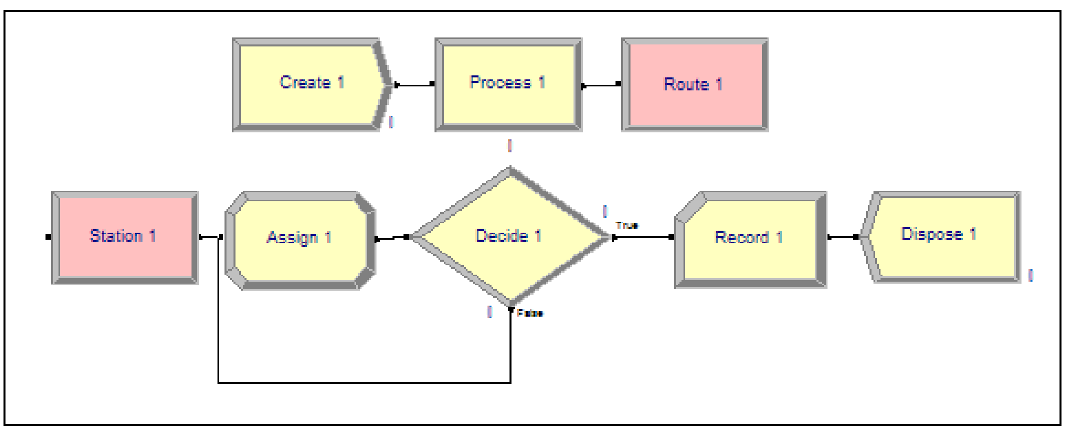


Figure 2: ARENA Modules

These modules are then ordered and networked together using *connects*. The connects identify the path and direction along which the entity should proceed. This section outlines the basic functions of ARENA used in this research as described by Kelton et al. (2003) and the ARENA User's Guide (Rockwell, 2007a).

The *create* module controls the arrivals of the entities that move throughout the simulation. The create blocks allow the user to specify a schedule on which the entities are created, the probability distribution that controls the time between arrivals and the probability distribution that controls the number of entities that occur per arrival. Each create module allows the modeler to specify the type of entity being created and whether it is an item moving through an assembly line, a customer moving through a queue or any other item of interest to the user.

The *process* module allows the user to delay an entity moving through the simulation according to a specified probability distribution. The module also allows users to seize, or exhaust, necessary resources required to perform the process. For example, in a customer service system, a customer service representative could be seized for the duration of the service and then be made available or released for subsequent customers. If the entities overwhelm the available resources, a queue is initiated to hold the entities for the next available resource.

The *route* and *station* modules provide an alternative method to connecting modules. A station identifies a location to which entities are transferred in the model. When an entity reaches a route module, it is relocated to the appropriately identified station module. This allows the user to transport entities between different sections of the model without having connects. The feature has many useful applications and is especially useful in this model for organizing the model into comprehensible sections.

The *assign* module allows the user to assign or change current attribute, entity or variable values specified in the simulation. An attribute is a value specific to an entity. For example, the time at which an entity is created is a value specific to a single entity or an entity attribute. This value and many others are automatically recorded by ARENA for every entity. Additional attributes can be specified by the user in order to identify specific information needed for analysis. For example, in a customer service queue, an attribute could be randomly assigned to identify the level of importance of each customer. This attribute could then be used to service customers according to their level of importance. It could also be used to divide the entities and gather statistics on the amount of time each type of customer spent in the queue. System variables can also be set and changed with each entity that passes through an assign module. An example is the number of customers in a particular servicing queue. If the number of customers meets a certain level, the assign module could be used to increase the number of representatives available to serve. Finally, the entity type can be manually changed through the assign module. This function allows users to specify and characterize an entity as it moves through the system. For example, suppose in a manufacturing system, entities move through the system and are serviced and combined with other entities to create new products or entities. The entity type can be adjusted accordingly.

The *decide* module enables decision making to occur in the simulation. The decisions can be made based on chance or by specified conditions. The decisions made by chance allow the user to identify any number of successive paths based on a specified percentage. For example, a simulation of a traffic system could decide that 60% of vehicle operators chose to take the freeway to a particular destination, 30% chose to take an alternate highway and 10% chose to use residential roads to reach the same destination. The decisions by condition allow the user to specify any number of conditions to route the entities to their subsequent destination. These conditions can be based on system variables, entity types or entity attributes. Using the same example of a traffic system, the vehicles could be routed based on a pre-assigned entity attribute. For example, passenger vehicles could be routed along one path while cargo vehicles could be routed along another path. Complex expressions can be developed to represent the decision process.

Finally, *record* modules are used to gather and record information that is not already gathered by ARENA. This allows the user to gather information that is specifically related to their analysis. Statistics can be gathered for the amount of time an entity spends in a certain section of the model or record the value of an entity's attribute at a specific location in the simulation. Statistical values such as the minimum, maximum and average values will then be automatically reported in the output statistics of the simulation. All gathered values can also be recorded to a specified file to be available to the analyst and decision maker for further analysis.

Simulation

The ARENA software was used to produce a simulation that models aerial cargo movements into Afghanistan through the defense transportation system. The model is divided into four distinct sections: *Entity Creation*, *Routing*, *Transloading*, and *Statistics*. The entities in the simulation are individual pallets of cargo. The Entity Creation section is responsible for generating all pallets and moving them to the next section. The Routing section determines the pallet's subsequent APOD and appropriately assigns a value for the length of time required to travel from an APOE to the APOD. The Transloading section determines whether the pallet will continue on to another destination or end at the current APOD. The Statistics section is used to divide the entities and gather statistics that are used in the analysis.

The entities are created in the *Entity Creation* section shown in Figure 3.

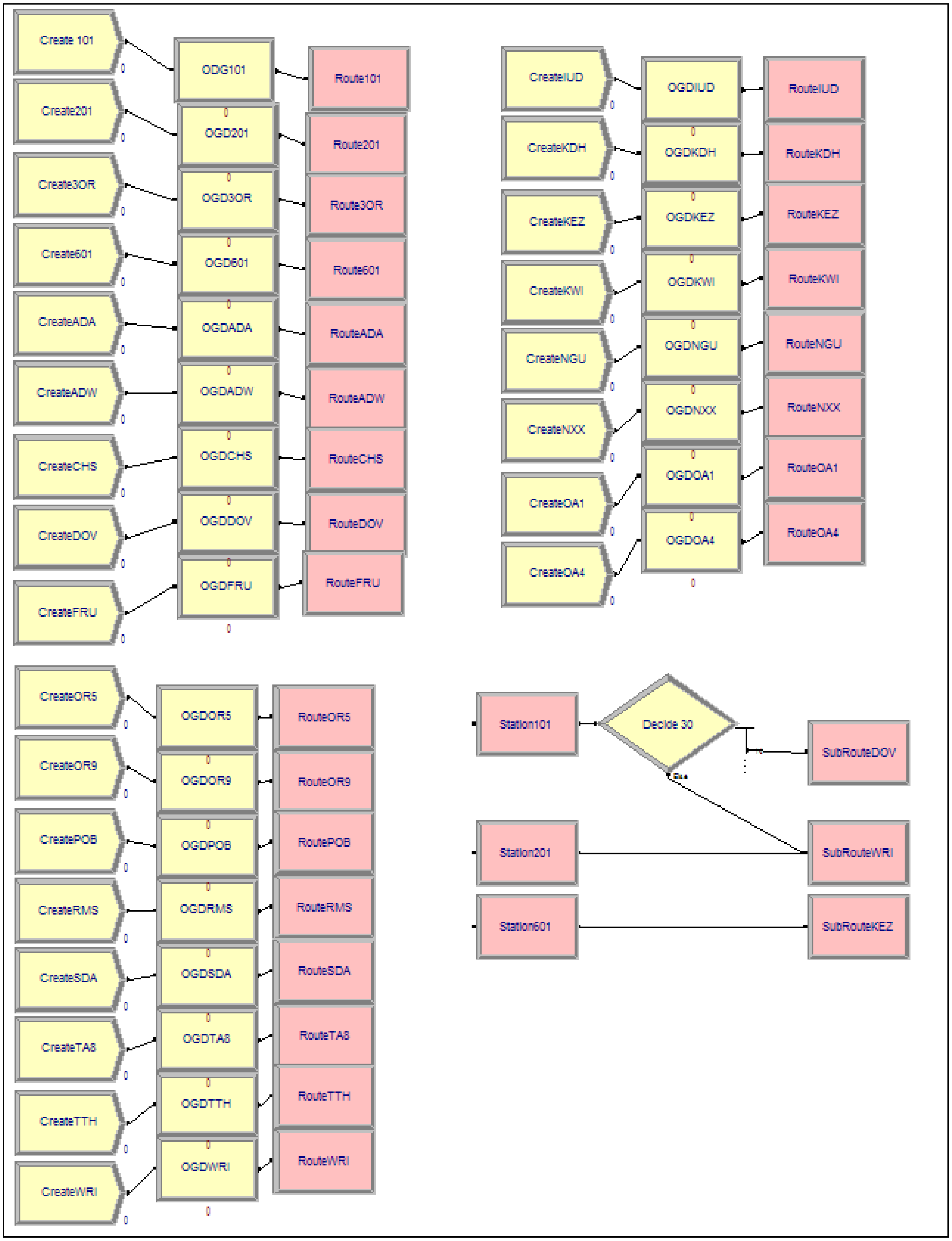


Figure 3: Entity Creation

Create modules were used to approximate arrivals of pallets into the system at each of the 25 retained APOEs. Each APOE creates a single pallet with the time between arrivals following an exponential distribution. The exponential distribution for each create module is designed to generate the same amount of arrivals as the port typically generates per day. The exponential distribution is commonly used to approximate the length of time between arrivals in a Poisson process. The Poisson process assumes that the arrival of pallets into the system is by a random process in which the arrivals are independent of one another.

Theoretically, after a pallet is built, it is registered and recorded in a database. From this point, the pallet will wait for the aircraft, crew and other equipment to become available for its transport. It is typically also delayed to be grouped with other pallets intended for destinations in the same area. The time a pallet spends on the ground at its APOE is another statistic that is easily gathered from the data used in this research. These delays were extracted for each of the 25 chosen APOEs and fit to a distribution. A process module was used to delay each of the pallets according to the distribution common to its APOE. The distribution selected for use in the delaying process was the lognormal distribution. This distribution is limited to only positive values which is appropriate for this process. It is therefore also positively skewed and centered about the mean. This behavior closely resembles the distribution of delays at the APOE and is used for each of the on ground APOE delays in the model.

The final function of the Entity Creation section is transferring each pallet to the proper location in the subsequent section of the model, Routing. Each of the 25 APOEs has a route module that transports the pallets to a corresponding station in the Routing section. Three of the APOEs are unique because the first air leg of their routing begins at another APOE. They are referred to by their APC as 101, 201 and 601. An additional sub-section of logic in the Entity Creation section of the model preliminarily routes the pallets originating at these ports to the first leg of their transportation which begin predominantly at the APCs of DOV, WRI, and KEZ.

The *Routing* section of the model contains the network of all probable connections of aerial ports between the APOE and APOD for each of the pallets. Each pallet in this section begins at the station corresponding to their APOE as shown in Figure 4. A decide module then determines which AP it will travel to next. A process module is used to delay each pallet according to a triangle distribution that approximates the duration of travel from the specified APOE to APOD.

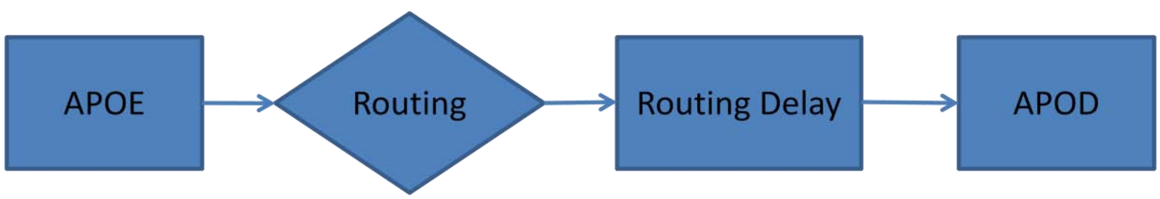


Figure 4: Routing Section Flowchart

An image of the simulation routing section is shown in Figure 5. The stations are located under the two columns labeled “APOE” shown on the left and right hand side of the figure. From each of these stations pallets move inward to their APOD under the column labeled “APOD” following the same logic displayed and explained previously in Figure 4.

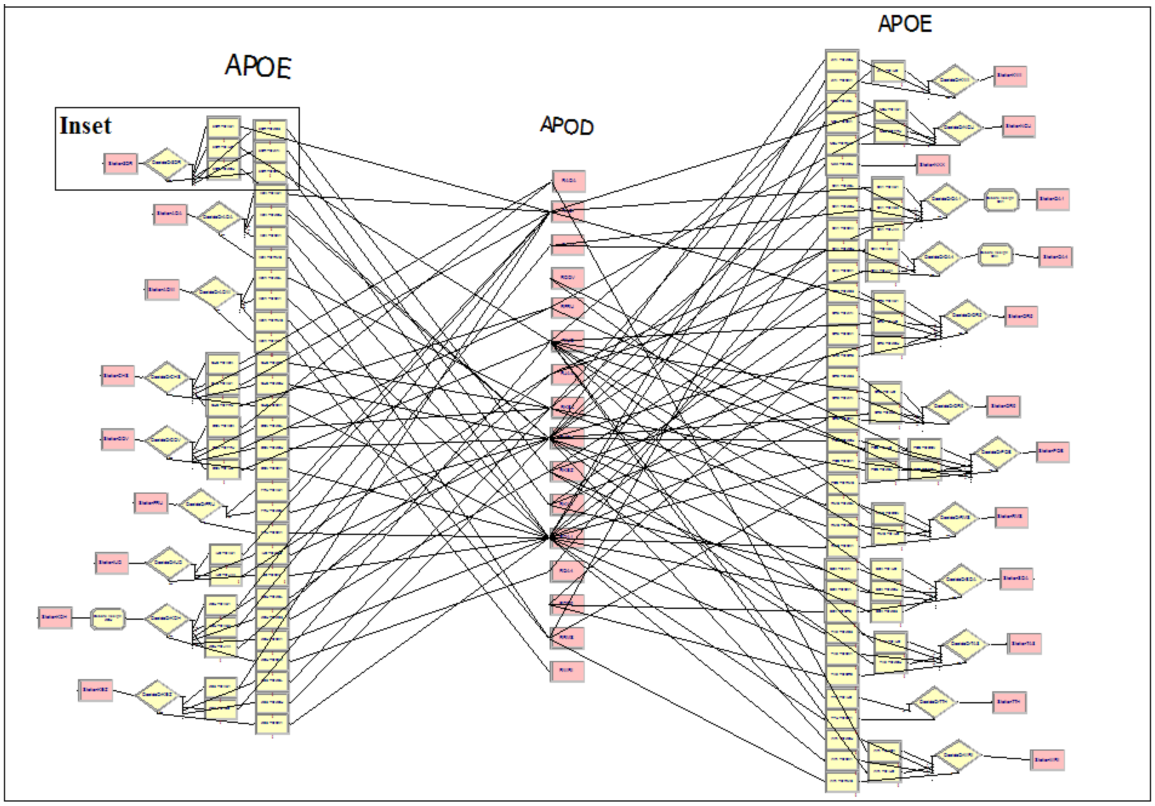


Figure 5: Routing

An inset of Figure 5 can be seen in Figure 6. It displays the station at which the pallet arrives, the decide module that routes the pallet to its next APOD and the process modules that simulate the amount of time it takes to travel from the APOE to APOD. It also shows the connects that continue to the next routing station that transfers the pallets to the subsequent section.

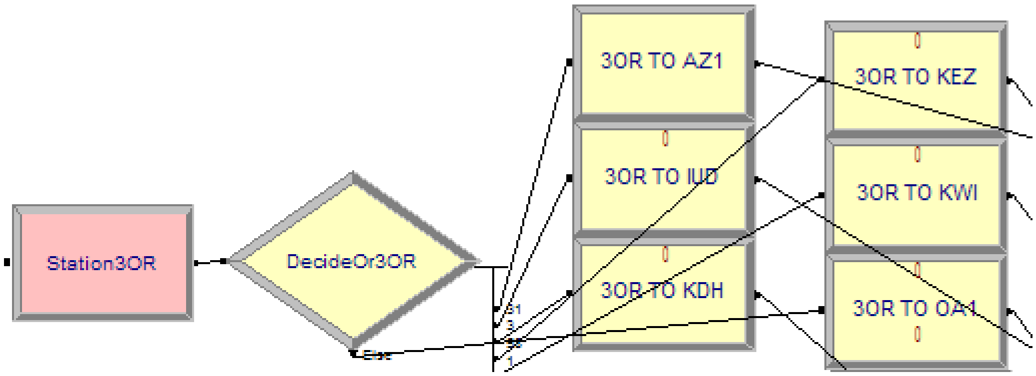


Figure 6: Routing Inset

This section contains a total of 22 APOEs and 16 APODs. The pallet then moves through a decide module. Each of the decide modules routes the pallets according to a percentage representing the normal routing of pallets. In ARENA, a random number between zero and one is assigned to each entity passing through the decide module and the entity is routed based on that number. For example, if 50% of the entities are routed along the first path and the rest are routed along the second path, any random number assignment less than 0.5 would be assigned to the first path. The decide module for each of the APOEs routes the pallet to a subsequent process module corresponding to the APOD that was selected. These process modules are labeled in all capital letters according to their APC in the ARENA simulation. For example, a pallet shipped from Dover AFB, Delaware to Incirlik AB, Adana Turkey is labeled "DOV TO ADA." Each of these process modules delays the pallet according to a triangular distribution. The triangular distribution is defined by three values: the minimum value, maximum value and modal value. The modal value is the most frequently occurring value in a series. The mean is substituted for the modal value if each value occurs only a single time. The mean of this distribution is therefore $\frac{a+b+c}{3}$, where a is the minimum value, b is the maximum value and *c* is the modal value. These distributions were based on values extracted from the database for each of the possible connecting routes between APOEs and APODs. After processing, each pallet is directed to the APOD route module. This module transports the individual pallets to the subsequent section, Transloading.

The *Transloading* section is responsible for determining the subsequent routing that is required for each pallet to reach its final destination or pallet APOD.

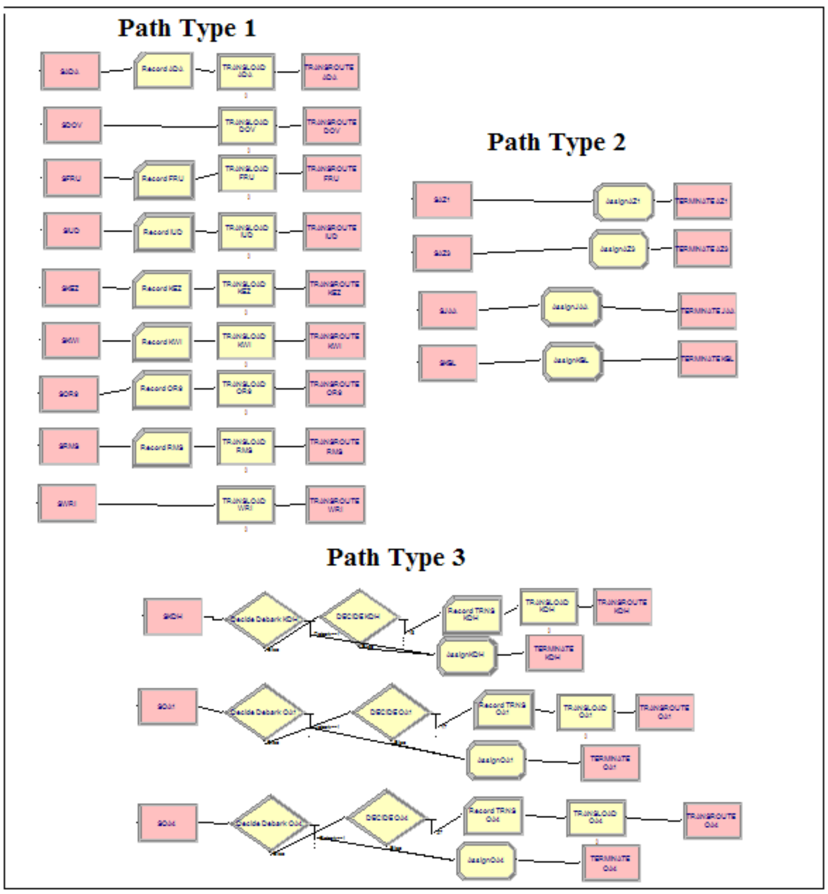


Figure 7: Transloading

There are 16 stations designated by the square modules located on the left side of each logic segment shown in Figure 7, corresponding to the 16 APOD route modules in the

Routing section. The Transloading section contains three different categories of paths. Path Type 1 includes pallets that will be transloaded. Path Type 2 handles pallets that are terminating or have reached their pallet APOD. Path Type 3 includes pallets that will either be transloaded or terminated.

The station modules in the paths that require transloading, Path Type 1, are followed by a record module that enables the capture of the number of entities that are transloaded through a specific AP. It is then sent to a process module that captures the time the pallet spends on the ground awaiting the aircraft, crew and other resources before it is rerouted to another destination. As was previously stated, these delays have been extracted from the GATES data set provided and fit to appropriate distributions. In this case, the distributions for each of the transload process modules are fit to a lognormal distribution. The entity then proceeds to a route module that routes it back to the corresponding APOE station in the Routing section. These two sections will continue to repeat this process until the pallet reaches its destination APOD.

Pallets that have reached their APOD, Path Type 2, pass through an assign module that assigns a value identifying the pallet's APOD. This allows important statistics about the total transit time to be gathered according to APOD. Next, the entity is sent to a route module that transports it to the appropriate station in the Statistics section of the model.

The APs of KDH, OA1, and OA4 are the three APs at which it must be determined whether the pallet will be rerouted to a subsequent destination or will terminate at the current APOD, Path Type 3. If the pallet is terminated, it follows the same logic as described in the previous paragraph and will be routed to the Statistics section after assigning the appropriate value for its APOD. Otherwise, it will be transloaded to the Routing section where the subsequent APOD will be determined. This process will be repeated between the Routing and Transloading section until the pallet reaches its destination APOD.

Two decision modules are located in each of these three paths. The first decision module determines, by condition, if the pallet originated in Afghanistan. If the pallet originated at an AP in Afghanistan, it will only have a single leg of transportation; it will be carried directly to its pallet APOD at another AP in Afghanistan. This value was pre-assigned in the Routing section. The second decision module determines by chance whether the pallet has reached its destination APOD and reroutes it to the Routing section or Statistics section, accordingly. These probabilities were also extracted from the dataset.

The *Statistics* section contains a station that gathers all the terminating entities and a decision module that divides them according to their APOD shown in Figure 8.

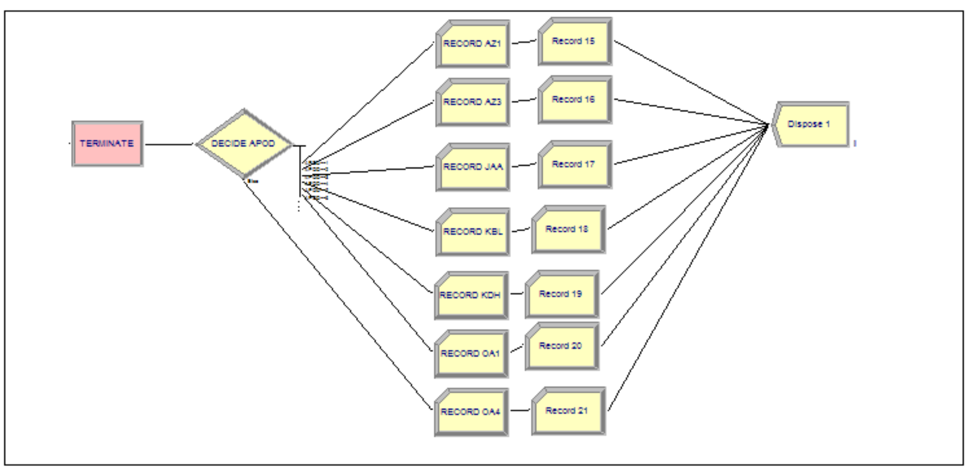


Figure 8: Statistics

There are two record modules for each pallet APOD. The first record module records the total time that the entity was in the transportation system. Statistics for this value are then reported in the output files. Each entity value is also recorded in a data file that is accessible after the model is complete for further analysis. The second record module counts the number of entities that terminate at each of the pallet APODs and are reported in the ARENA output files.

Simulation Model Validation

Simple validation of the model was performed in order to determine if the simulation was accurately modeling several different factors. The items that were validated in the simulation are the number of pallets created at each of the pallet APOEs, the number of pallets transloaded at each of the transload hubs, the number of pallets delivered to each pallet APOD (as its final destination), the cargo delivery time mean for each pallet APOD and the cargo delivery time standard deviations for each pallet APOD. The comparison of these measures' historical and modeled values indicates the validity of the simulation model and the results and analysis presented. The modeled values are the average for that statistic over 30 replications of the base case simulation. The simulation was replicated 30 times in order to increase statistical confidence; fewer replications can cause the computed confidence interval for the statistic to be greater than it should be. Each replication simulated a period of 365 days.

The number of pallets created per day at each of the pallet APOEs is shown in Table 6. The historical and modeled values for pallets created are quite similar. This is expected since pallet creation is the first activity in the simulation; no activity goes uncaptured at this point in the model that could lead to large differences in observed values. The greatest difference between the historical and modeled data is only 2.44%.

Table 6: Validation, Pallets Created

Pallet APOE	Pallets Created (Per Day)		
	Historical	Model	Difference
101	3.01	3.03	0.66%
201	0.28	0.29	3.57%
3OR	1.42	1.43	0.70%
601	2.08	2.09	0.48%
ADA	0.21	0.21	0.00%
ADW	0.21	0.20	4.76%
CHS	8.70	9.11	4.71%
DOV	10.09	10.04	0.50%
FRU	0.34	0.34	0.00%
IUD	6.34	6.27	1.10%
KDH	2.92	2.93	0.34%
KEZ	12.25	12.47	1.80%
KWI	4.95	4.99	0.81%
NGU	3.38	3.31	2.07%
NXX	0.24	0.24	0.00%
OA1	5.79	5.86	1.21%
OA4	1.04	1.05	0.96%
OR5	0.74	0.75	1.35%
OR9	1.47	1.48	0.68%
POB	2.54	2.59	1.97%
RMS	1.62	1.62	0.00%
SDA	0.53	0.54	1.89%
TA8	0.25	0.25	0.00%
TTH	0.23	0.22	4.35%
WRI	16.68	16.67	0.06%

The number of pallets transloaded per year for each transload hub modeled in this simulation is shown in Table 7. These values indicate that the proper cargo amount is transitioning at each of the transload hubs. Most of the results are within 10% of the historical value. The two transload hubs that are above 10% are the two smallest or least utilized transload hubs in this network. Differences in historical and modeled values could be due, in part, to rounding. Routing of cargo from the APOE was determined to a percentage rounded to a whole number. Therefore transload hubs could experience some differences in expected number of deliveries which could cause slight differences in observed data.

Table 7: Validation, Pallets Transloaded by Transload Hub

Transload Hub	Pallets Transloaded (Per Year)		
	Historical	Model	Difference
OA1	3202.40	3378.19	5.49%
IUD	1903.37	2093.51	9.99%
ADA	1500.95	1420.30	5.37%
KDH	932.62	896.62	3.86%
KEZ	385.47	352.29	8.61%
FRU	224.51	238.04	6.03%
KWI	206.15	210.06	1.89%
RMS	168.73	148.97	11.72%
OR9	60.01	52.01	13.33%

The historical and modeled value for the number of pallets delivered to each of the pallet APODs are listed in Table 8 along with the percent deviation between each pair. Again, the historical and modeled observations are similar. Deviations are due, in part, to rounding of routing percentages at the pallet APOEs and transload hubs for each pallet and other un-modeled activities.

Table 8: Validation, Pallets Delivered by APOD

Pallet APOD	Pallets Delivered (Per Year)		
	Historical	Model	Percent
AZ1	1980.32	2199.98	11.09%
AZ3	1219.96	1276.14	4.61%
JAA	1716.98	1882.02	9.61%
KBL	2622.07	2791.04	6.44%
KDH	4394.83	4519.27	2.83%
OA1	18632.6	18071.3	3.01%
OA4	1301.86	1367.51	5.04%

The historical and modeled mean delivery time at each APOD are listed in Table 9. The values for historical and modeled data are similar; however, differences are also apparent. For example, the modeled mean delivery times at JAA, KDH, OA1 and OA4 differ by more than 5% from their historical observed values. These differences are due, in part, to the distributions used for APOE port hold times, transload times and flight times between APs. As previously indicated, port hold times and transload times use a log normal distribution while flight times use triangular distributions.

Table 9: Validation, Delivery Time Mean by APOD

Pallet APOD	**Delivery Time Mean (Days)**		
	Historical	Model	Difference
AZ1	6.40	6.34	0.94%
AZ3	7.48	7.79	4.14%
JAA	7.51	7.93	5.59%
KBL	8.97	9.06	1.00%
KDH	6.38	6.74	5.64%
OA1	5.41	5.96	10.17%
OA4	7.19	7.71	7.23%

The historical and modeled delivery time standard deviations also show many similarities. The historical and modeled observations as well as the difference between the two are shown in Table 10. Although some of the observations are within 2% of the historical value, others, such as AZ3, KBL, KDH, and OA4, differ by as much as 11%. Differences, in part, are likely due to the distributions used to model APOE port hold times, transload times and flight times between APs. The APOE port hold times and transload times use fitted log normal distributions. The flight times are approximated using triangular distributions. These approximations and other non-modeled activities within the simulation cause differences in the observed model delivery time standard deviation.

Table 10: Validation, Delivery Time Standard Deviation by APOD

Pallet APOD	Delivery Time Standard Deviation (Days)		
	Historical	Model	Difference
AZ1	6.24	6.15	1.44%
AZ3	6.40	6.85	7.03%
JAA	6.78	6.89	1.62%
KBL	7.24	6.54	9.67%
KDH	5.46	5.98	9.52%
OA1	5.73	5.56	2.97%
OA4	6.13	6.83	11.42%

Process Analyzer

The Process Analyzer (PAN) is companion software that works in conjunction with ARENA to further investigate a model. When an ARENA model terminates, it produces a ".p" file which is compatible with the PAN. The PAN allows users to specify scenarios, controls and responses in order to perform several replications for a designed experiment or other analysis. The scenario is the ".p" file or ARENA model used in these analyses. The controls are the variables in the ARENA model which users may change. The responses are the values that the ARENA model records which are of interest to the user. The PAN is used after the model has been correctly configured and validated. It can be a great aide to analysts and decision makers by allowing them to specify input controls in the model and observe the subsequent responses (Kelton et al., 2003; Rockwell, 2007a).

Process Analyzer Design

A 2^5 full factorial designed experiment was performed using the Process Analyzer that included five factors and one center point. This produces 33 design points to be modeled. The controls used in conjunction with the simulation are the transload time standard deviations for the distributions of each of the five busiest transload hubs in the model. The responses are the levels of standard deviation at each of the seven pallet APODs in Afghanistan. The lower values in the design are set to 50% of the historical value. The upper values are set to 200% of the historical value. The center point values are set to the historical values. Table 11 shows the lower, upper, and base case levels used in the design.

Table 11: Full Factorial Design Levels

Transload Std Dev (Days)	Lower (-)	Base Case (0)	Upper (+)
OA1	2.24	4.48	8.96
IUD	4.31	8.62	17.24
ADA	2.32	4.64	9.28
KDH	1.22	2.43	4.86
KEZ	2.38	4.76	9.52

Each of the 33 design points was replicated 30 times and the average value for each treatment combination was used in the model. Each design point was replicated 30 times in order to increase confidence in the statistic and coordinate with results from the preceding analysis.

OptQuest

OptQuest is an additional application for ARENA produced by OptTek Systems Inc. This software attempts to maximize or minimize an output performance measure based on the inputs defined by the user. The following paragraphs explain OptQuest's functionality and capabilities as described by Laguna (1997) and Glover et al. (1999) as well as the *OptQuest for ARENA User's Guide* (Rockwell, 2007b). Additional information about the system can also be referenced in both of these articles.

The OptQuest software integrates an ARENA simulation with user specified controls, responses and constraints to search the solution space for optimal model configurations. It completes several simulations, varying inputs, in an effort to find superior areas of the solution space. It is similar to the Process Analyzer in that it is able to automatically vary the inputs of an ARENA model; however, it differs by choosing its own progression of inputs instead of relying on user defined input values.

The controls are the input variables that OptQuest can vary. Both system and user specified variables are automatically available for selection as controls. Each control must be defined by type: continuous, binary discrete or integer. A lower bound, upper bound and suggested value are also required according to type. The optimization initiates at the user-defined suggested value. The closer the suggested values are to the optimal solution, the quicker the optimization will, in general, converge to an optimal solution. Any number of controls can be selected; however, as the number of controls increases, the quality of the solution deteriorates. The OptQuest for ARENA help guide indicates that the performance of OptQuest might deteriorate if using more than 100 controls. Other alternatives to be considered when performing an optimization with a large number of controls include: reducing the number of replications in order to increase the number of simulations, restricting the bounds on the controls and repeating the optimization process.

Responses are the output performance measures monitored in the optimization. Again, all system and user defined responses are automatically available in OptQuest and may be monitored for each replication of the simulation. Responses can be monitored even if they are not used as constraints or the objective function.

Constraints are functions of the controls and responses that have been selected in the optimization. OptQuest classifies each constraint as linear or non-linear. Prior to running a simulation, it validates that the linear constraints are not violated. The objective function defines the goal of the optimization. The objective function allows users to minimize or maximize a function of the previously selected controls and responses. OptQuest allows users to define numerous objective functions but will only allow one to be optimized at a time. Each objective function will have to be evaluated independently. OptQuest is able to effectively evaluate complex objective functions. It is designed to find a global optimum even if the objective function has numerous local minimums or maximums. Decisions in control values are based on heuristics known as tabu search and scatter search as well as other methods to intelligently move throughout the solution space (Glover et al., 1999).

Heuristics are strategies (in this case algorithms) that use different techniques and available information to solve problems. OptQuest uses these methods to efficiently find good solutions. The first type of heuristic utilized by OptQuest is tabu search. It uses an iterative method to develop a new feasible solution from the current solution. The objective function value of the solution is determined and the process repeated. At each process iteration, the current solution or some attribute thereof is placed on the tabu list. The tabu list prevents the algorithm from selecting a feasible solution that is already on the list for some iteration interval. This prevents the algorithm from returning to recently visited solutions and increases the possibility of exploring more of the solution space. These algorithms are also capable of selecting non-improving objective function values which allow them to escape from local minima (Aarts and Lenstra, 2003).

The second type of heuristic OptQuest utilizes is scatter search. Scatter search is classified as an evolutionary heuristic or genetic algorithm. Genetic algorithms are unique because they consider a population of possible solutions at once instead of considering individual solutions iteratively. Genetic algorithms attempt to optimize the fitness of the population of possible solutions by combining and mutating characteristics of the current set of solutions (Aarts and Lenstra, 2003). In a scatter search heuristic, a diverse set of solution vectors is generated as a starting point. Other heuristic methods selected by the operator are then utilized to further improve each individual solution vector. A set of the *b* best solutions is then designated as reference solutions. New solutions are created using structured combinations of subsets of the current reference solutions. These solutions are further improved using the operator chosen heuristic methods. A collection of the best improved solutions is added to the reference set. Then, the reference set is reduced to the *b* best solutions and the process is repeated for a specified number of iterations (Glover et al., 2000). The combination of these two heuristic procedures allows OptQuest to intelligently search for good solutions. Unfortunately, this procedure does not typically provide an optimal result or acknowledge an optimal result if one is found.

One method by which OptQuest generates an initial set of solutions is through suggested solutions from the analyst. Additional suggested solutions can be added to the optimization in an attempt to increase the possibility of quick convergence to near optimal results. Suggested solutions can be based on expert opinion, previous solutions or any other insight available to the user. Solutions from the best solutions tab can be added to the suggested solutions for subsequent optimizations.

The options menu for each simulation allows the user to specify criteria for ending the optimization, a tolerance level for discriminating between results, the number of replications per simulation and a file for storing the log of solutions discovered throughout the optimization. The criteria for terminating a search with OptQuest are also user defined. The search can be conducted for a certain number of replications. The algorithm can perform only the suggested solutions or it can be automatically stopped by OptQuest. The first two criteria are intuitive. The third criterion, automatic stop, terminates the search after 100 replications have been performed without an objective function value improvement.

The number of replications per simulation can be set to a finite number or bounds for the minimum and maximum replications can be defined. The minimum number of replications is performed, and a 95% confidence interval is constructed. If the upper bound on the confidence interval is better than the current best available solution, a subsequent replication of the simulation is performed and the process is repeated until the simulation scenario is deemed inferior or the maximum number of replications is completed.

Finally, a log of solutions is kept for each of the different scenarios performed in the optimization. The values for the controls and responses for each of the scenarios completed are recorded in the log. The solutions log is in a comma separated format which allows the data generated from the optimization to be easily integrated with most other software data packages.

OptQuest Design

Several different optimization designs were used in OptQuest to further explore the simulation model created in ARENA. As previously stated, OptQuest allows the user to specify controls, responses, constraints and objective functions for each optimization. Table 12 highlights the various controls used throughout the different scenarios. A description and initial value are given for each of the controls. The initial value measured in days is the value used in the original simulation; the initial value is also used as the suggested value in each of the different scenarios.

Table 12: Controls

Control	Initial Value (Days)	Description
μ_{T-ADA}	4.82	Transload time mean at specified location
μ_{T-IUD}	2.58	
μ_{T-KDH}	3.62	
μ_{T-KEZ}	4.12	
μ_{T-OA1}	3.48	
μ_{O-CHS}	3.49	Pallet APOE time mean at specified location
μ_{O-DOV}	3.49	
μ_{O-IUD}	2.97	
μ_{O-KEZ}	4.00	
μ_{O-KWI}	3.62	
μ_{O-WRI}	2.74	
σ_{T-ADA}	4.64	Transload time standard deviation at specified location
σ_{T-IUD}	8.62	
σ_{T-KDH}	2.43	
σ_{T-KEZ}	4.76	
σ_{T-OA1}	4.48	
σ_{O-CHS}	3.73	Pallet APOE time standard deviation at specified location
σ_{O-DOV}	3.33	
σ_{O-IUD}	3.41	
σ_{O-KEZ}	4.01	
σ_{O-KWI}	3.82	
σ_{O-WRI}	2.73	

The controls can be classified into four distinct groups. The first and second groups are the mean transload times at the five busiest transload ports and the transload time standard deviations for the same ports, respectively. The third and fourth groups are the mean times before departure at each of the six busiest ports of origination and the standard deviations for the same six ports. Table 13 highlights the responses considered in the analysis. They include the mean delivery time for each pallet APOD and the delivery time standard deviation for each pallet APOD.

Table 13: Responses

Response	Description
μ_{AZ1}	Cargo delivery time mean for specified location (Days)
μ_{AZ3}	
μ_{JAA}	
μ_{KBL}	
μ_{KDH}	
μ_{OA1}	
μ_{OA4}	
μ_{TOT}	Sum of the means for all cargo delivery locations
σ^2_{AZ1}	Cargo delivery time variance for specified location (Days^2)
σ^2_{AZ3}	
σ^2_{JAA}	
σ^2_{KBL}	
σ^2_{KDH}	
σ^2_{OA1}	
σ^2_{OA4}	
σ^2_{TOT}	Sum of the variance for all cargo delivery locations

This section elaborates on the controls and responses selected for each of the scenarios investigated.

Scenario 1

Scenario 1 utilizes the standard deviations of the distributions at each of the five busiest transload stations in order to minimize the total delivery time variance of all cargo shipped to an Afghanistan APOD. Table 14 shows the upper, lower and suggested values (in days) for each of the controls used in the scenario.

Table 14: Controls, Scenario 1

Control (Days)	Lower Bound	Suggested Value	Upper Bound
σ_{T-ADA}	2.32	4.64	15
σ_{T-IUD}	4.31	8.62	15
σ_{T-KDH}	1.22	2.43	15
σ_{T-KEZ}	2.38	4.76	15
σ_{T-OA1}	2.24	4.48	15

Two constraints were used in this scenario.

$$\sigma_{T-ADA} + \sigma_{T-IUD} + \sigma_{T-KDH} + \sigma_{T-KEZ} + \sigma_{T-OA1} \geq \beta$$

$$\sigma_{T-ADA} + \sigma_{T-IUD} + \sigma_{T-KDH} + \sigma_{T-KEZ} + \sigma_{T-OA1} \leq \delta$$

Where $\beta = 24.93$ (the summation of the transload time standard deviations) and $\delta = 40$. The parameter δ was set at 40 in order to prevent the OptQuest scenario from testing configurations of the system with cumulative amounts of transload time variance in excess of 1600 days^2. This value was selected based on previous experience with the software and recommendations from the *OptQuest for ARENA User's Guide* (Rockwell, 2007b). The *User's Guide* suggests that eliminating configurations that are clearly not part of the optimal configuration can result in increased efficiency of the software. The first constraint requires that a certain level of variance in the transload time distributions be maintained. The second constraint limits the available solution space so that the OptQuest search may converge more quickly to high quality solutions. This allows the scenario to shift the variance in transload time to the hub that causes the least amount of total variance in delivery time.

In this scenario, optimization was conducted primarily for the response σ^2_{TOT}, total delivery time variance; however, separate optimizations were also performed for each of the seven pallet APODs. After completing the optimization of σ^2_{TOT}, various optimal solutions were added to the suggested solutions to increase likelihood of convergence to the optimal solution in the subsequent simulations. The results are summarized and presented in Chapter IV.

A total of 200 simulation instances of *Scenario 1* were completed. The confidence interval method was used to determine the number of replications to perform for each simulation instance. In this method, five replications of the same simulation instance are performed. Next, a 95% confidence interval is performed on the first five replications to determine if more replications of the simulation instance were required. If the bounds on the confidence interval contain the current best solution, the instance is terminated; otherwise, another replication is performed. This process is repeated until the bounds on the confidence interval no longer contain the current best solution or the maximum number of replications, 15, is reached. The maximum number of replications prevents OptQuest from becoming trapped on a particular simulation instance. OptQuest can return to previously used control values and evaluate two different sets of control values that have remarkably similar response values. These two possibilities could cause OptQuest to replicate a simulation instance numerous times before moving on to the next simulation instance.

Scenario 2

Scenario 2 utilizes the mean delay times at the six busiest pallet APOEs and the five busiest transload stations in order to minimize the total delivery time variance of all cargo shipped to an Afghanistan APOD. Table 15 shows the upper, lower and suggested values for each of the controls used in the scenario.

Table 15: Controls, Scenario 2

Control (Days)	Lower Bound	Suggested Value	Upper Bound
μ_{T-ADA}	4.82	4.82	10
μ_{T-IUD}	2.58	2.58	10
μ_{T-KDH}	3.62	3.62	10
μ_{T-KEZ}	4.12	4.12	10
μ_{T-OA1}	3.48	3.48	10
μ_{O-CHS}	3.49	3.49	10
μ_{O-DOV}	3.49	3.49	10
μ_{O-IUD}	2.97	2.97	10
μ_{O-KEZ}	4.00	4.00	10
μ_{O-KWI}	3.62	3.62	10
μ_{O-WRI}	2.74	2.74	10

This scenario is used to determine if there is a synchronization of port hold times that could be used to reduce delivery time variance. Variance in delivery time also occurs as a result of the difference in mean delivery times for different channel routes. By changing the port hold time means for each of the controls specified, the variance total may be reduced. This scenario is able to determine if port hold times can be adjusted and synchronized in such a way that the mean delivery times along channel routes are more similar. If so, the delivery time variance will be reduced. As shown in Table 15, the lower values for this scenario are the same as the mean values derived from the database. In other words, a reduction in mean port hold time is not allowed. No additional constraints were used in this scenario.

Since this scenario has 11 different controls, 500 simulation instances are performed for the response σ_{TOT}^2, the sum of the pallet APOD variances. Again, for each instance, a minimum of five replications are performed. A total of 200 simulation instances were performed for the other pallet APOD responses listed in Table 13. The confidence interval method was used to determine the number of replications for each simulation instance in this scenario.

Scenario 3

Scenario 3 extends the scope of *Scenario 1*. *Scenario 3* utilizes the transload time standard deviations shown in Table 13 as well as the transload time standard deviations for the six busiest pallet APOEs in order to minimize the cargo delivery time variance. The controls and their settings are shown below in Table 16.

Table 16: Controls, Scenario 3

Control (Days)	Lower Bound	Suggested Value	Upper Bound
σ_{T-ADA}	2.32	4.64	15
σ_{T-IUD}	4.31	8.62	15
σ_{T-KDH}	1.22	2.43	15
σ_{T-KEZ}	2.38	4.76	15
σ_{T-OA1}	2.24	4.48	15
σ_{O-CHS}	1.87	3.73	15
σ_{O-DOV}	1.66	3.33	15
σ_{O-IUD}	1.71	3.41	15
σ_{O-KEZ}	2.01	4.01	15
σ_{O-KWI}	1.91	3.82	15
σ_{O-WRI}	1.37	2.73	15

Two constraints were used in the definition of *Scenario 3* shown below.

$$\sigma_{T-ADA} + \sigma_{T-IUD} + \sigma_{T-KDH} + \sigma_{T-KEZ} + \sigma_{T-OA1} + \sigma_{O-CHS} + \sigma_{O-DOV} + \sigma_{O-IUD} + \sigma_{O-KEZ} + \sigma_{O-KWI} + \sigma_{O-WRI} \geq \beta$$

$$\sigma_{T-ADA} + \sigma_{T-IUD} + \sigma_{T-KDH} + \sigma_{T-KEZ} + \sigma_{T-OA1} + \sigma_{O-CHS} + \sigma_{O-DOV} + \sigma_{O-IUD} + \sigma_{O-KEZ} + \sigma_{O-KWI} + \sigma_{O-WRI} \leq \delta$$

As in *Scenario 1*, the first constraint requires the total amount of variance throughout the system of transload hubs and pallet APOEs to be maintained at a minimum level. The second constraint reduces the solution space significantly by eliminating configurations of the system with combined control standard deviations greater than 65. This aids the search heuristics in converging to high quality solutions quickly. For *Scenario 3*, $\beta = 45.96$ and $\delta = 65$. Again, the parameter β is the sum of the base level standard deviations of the 11 controls used in this scenario. The parameter δ was selected based on previous experience with the software and this scenario. The sum of the upper bounds for the eleven controls is 165. This constraint guides OptQuest to the area where it is most likely to find local and global optimum while avoiding elimination of local and global optimum from the solution space.

The responses for this scenario include the delivery time variance for each of the seven pallet APODs as well as σ^2_{TOT}, the sum of the variances across all seven pallet APODs. A total of 500 simulation instances were performed for response σ^2_{TOT}, and 200 simulation instances were performed for each individual APOD variance. The confidence interval method was used in this scenario to allow OptQuest to search more of the solution space without requiring multiple replications of instances that are obviously inferior.

Scenario 4

Scenario 4 is a combination of *Scenario 2* and *Scenario 3*. It utilizes the transload time and pallet APOE time means shown in Table 15 and their respective standard deviations shown in Table 16 as controls. The same lower, upper, and suggested values used in *Scenario 2* and *Scenario 3* are used in this scenario. The constraints

$$\sigma_{T-ADA} + \sigma_{T-IUD} + \sigma_{T-KDH} + \sigma_{T-KEZ} + \sigma_{T-OA1} + \sigma_{O-CHS} + \sigma_{O-DOV} + \sigma_{O-IUD} + \sigma_{O-KEZ} + \sigma_{O-KWI} + \sigma_{O-WRI} \geq \beta$$

$$\sigma_{T-ADA} + \sigma_{T-IUD} + \sigma_{T-KDH} + \sigma_{T-KEZ} + \sigma_{T-OA1} + \sigma_{O-CHS} + \sigma_{O-DOV} + \sigma_{O-IUD}$$

$$+ \sigma_{O-KEZ} + \sigma_{O-KWI} + \sigma_{O-WRI} \leq \delta,$$

where $\beta = 45.96$ and $\delta = 65$, are also utilized in this scenario to maintain the baseline level of variance throughout the system and reduce the size of the solution space considered by OptQuest.

Since this is a more comprehensive design with 22 different controls, the response σ^2_{TOT} is first considered with 2000 simulation instances run. The *OptQuest for ARENA User's Guide* (Rockwell, 2007b) suggests using at least 2000 simulations for scenarios with 20-50 controls. The *User's Guide* suggests that, as the number of controls is increased, the number of simulations recommended grows at a greater than linear rate. Each of these simulation instances were only replicated three times each. The top five differing solutions resulting from this procedure are then added to the suggested solutions and the design is modified using the confidence interval method previously described with the minimum and maximum number of replications set to five and 15, respectively. The minimum and maximum number of replications balance the confidence of the statistics with the length of time required to run the simulation. By requiring only five replications, simulation configurations that are clearly inferior are performed quickly. The simulations that are near the optimal require more replications and increase the confidence in the statistics observed. The modified design was run for 500 simulation instances. Each of the seven other responses was then investigated using the modified design and 500 simulation instances each.

Summary

The methodology presented in this chapter provides the detailed procedures that were undertaken to thoroughly explore delivery time variance reduction as it pertains to the aerial component of military logistics. The following chapter outlines the results of each of the different methodologies previously described.

IV. Results and Analysis

This chapter describes the results and analysis conducted during this research endeavor. First, the variance analysis is reported for different cargo characteristics. Second, results from a designed experiment using the ARENA simulation software and Process Analyzer are described. Finally, the results from different OptQuest scenarios are reported.

Variance Analysis

The GATES data, as described earlier, is classified in many different ways. This section analyzes the distributions of the data based on aircraft type, pallet weight, pallet type and transload hub. The results indicate that delivery time distributions differ for each of the categories analyzed.

Aircraft Type

Various aircraft types are used to transport pallets within AMC. A summary of their qualities and capabilities is located in Chapter III. Table 17 lists the eight main aircraft types along with the pallet delivery time minimum, maximum, average and variance for every pallet that travelled one or more segments aboard the designated aircraft. Note that the average delivery time for cargo that travelled aboard non-military aircraft is significantly lower than cargo travelling aboard a C-5, C-17 or C-130. The cargo delivery time variance for non-military aircraft is also significantly less than that of the C-5, C-17 and C-130.

Table 17: Aircraft Type Data Summary

	Non-Military Aircraft				Military Aircraft			
	AN-124	B-747	DC-10	MD-11	C-5	C-17	C-130	KC-10
Min (Days)	1.87	0.96	1.01	0.86	1.44	1.02	0.71	1.04
Max (Days)	13.71	46.94	49.63	40.18	91.17	79.22	58.86	32.62
Average (Days)	4.59	4.60	3.85	3.75	9.53	7.08	9.25	4.69
Variance ($Days^2$)	2.99	11.57	8.88	8.56	44.55	30.71	54.14	12.97

A distribution, shown in Figure 9, illustrates the differences in cargo delivery times for four different aircraft types: the B-747, C-17, C-130 and KC-10. This depiction clearly identifies the differences in distributions. For example, the distribution for the KC-10 is tightly clustered around the mean while the distribution for the C-130 has a positive skew greater than that of any of the other distributions.

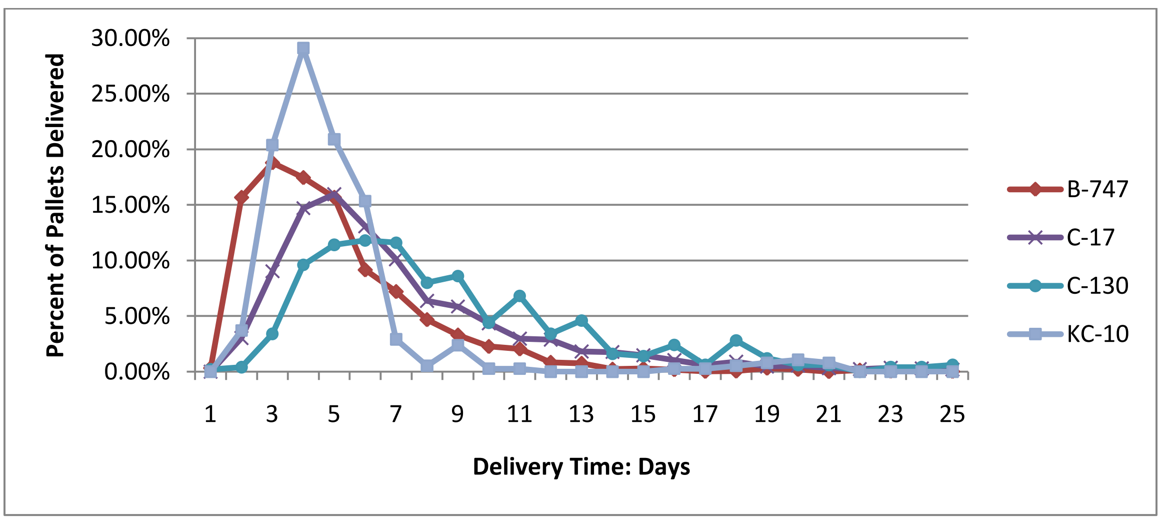


Figure 9: Distribution, Aircraft Type

Transload Hub

The data can also be classified by the transload hub through which it passes (if applicable). Table 18 shows six transload hubs through which the majority of transloaded pallets pass, and lists the cargo delivery time minimum, maximum, average and variance for each.

Table 18: Transload Hub Data Summary

	ETAR	LTAG	OAIX	OAKN	OTBH	UAFM
MIN (Days)	1.22	2.18	0.71	4.54	1.79	1.66
MAX (Days)	57.59	31.92	58.86	28.41	70.45	57.47
AVERAGE (Days)	10.69	8.28	9.34	11.97	6.19	3.71
VARIANCE (Days^2)	72.91	27.14	66.77	18.01	21.85	15.94

Figure 10 shows the distributions of three transload hubs. This depiction clearly indicates the differences in distributions that exist, specifically differences in variance. The delivery time for pallets transloaded at FRU is highly concentrated about the mean; there are very few pallets with a delivery time greater than seven days. On the other hand, pallets transloaded at IUD have less concentration about the mean, and there are several pallets with delivery times greater than seven days. Finally, the most positively skewed distribution, delivery times for pallets transloaded at OA1, has the least amount of pallet delivery times concentrated about the mean and the most pallets with deliveries greater than seven days.

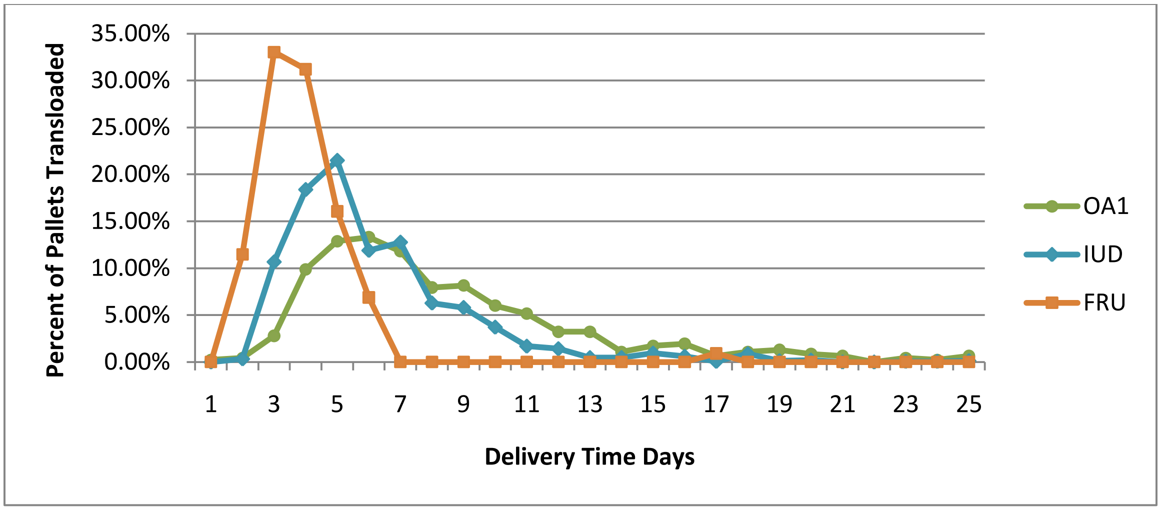


Figure 10: Distribution, Transload Hubs

Pallet Type Code

Table 20 shows the minimum, maximum, average and variance for cargo delivery time at the most utilized pallet type codes. The pallet type code definitions can be referenced in Table 5. While most of the mean delivery times for the different pallet type codes are quite similar, the differences in variance throughout are of particular interest. Variance for pallet type codes A, F, I, and S are comparatively much lower than the other pallet type codes.

Table 19: Pallet Type Code Data Summary

	A	B	E	F	G	I	L
MIN (Days)	1.02	0.71	0.96	1.00	1.28	1.94	0.96
MAX (Days)	43.03	57.47	79.22	15.37	49.17	21.02	91.17
AVERAGE (Days)	5.44	5.52	5.40	3.70	5.58	6.22	6.46
VARIANCE (Days^2)	12.95	25.39	29.49	4.63	15.09	10.69	27.25

	M	N	Q	S	T	Y
MIN (Days)	0.99	0.95	1.14	0.86	1.17	0.88
MAX (Days)	54.86	28.92	24.34	33.87	27.90	36.92
AVERAGE (Days)	9.51	3.85	5.40	3.85	6.53	6.83
VARIANCE (Days^2)	73.04	18.38	14.75	8.67	24.23	24.85

Figure 11 illustrates these differences in delivery time distributions. The distribution for type code M is unconventional and disjoint. Type code M defines cargo over 100 inches that must be transported by C-5. Fewer of this type are transported, and the availability of C-5 aircraft makes the variance for this type quite large. Type A and S both have delivery times concentrated about their mean with slight positive skewing.

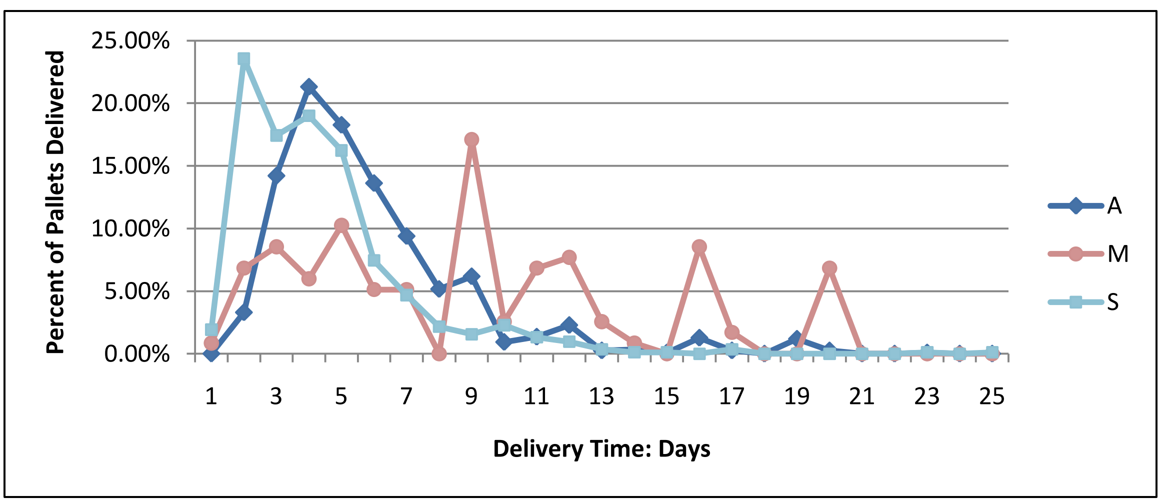


Figure 11: Distribution, Pallet Type Code

Pallet Weights

The values for delivery time minimum, maximum, average and variance are shown in Table 20. The variances are quite similar except for the group of cargo classified as greater than or equal to 20,000 pounds. Cargo weighing 20,000 pounds or more has a significantly lower variance compared to the other five categories.

Table 20: Pallet Weights (pounds) Data Summary

	< 2500	>=2500, <5000	>=5000, < 10000	>= 10000	>=20000	Aggregate
MIN (Days)	0.71	0.88	0.86	0.96	1.25	0.71
MAX (Days)	58.86	91.17	79.22	36.92	22.83	91.17
AVERAGE (Days)	4.84	5.69	6.60	5.96	4.90	5.74
VARIANCE (Days^2)	20.22	26.31	24.50	24.32	4.44	23.71

Figure 12 shows the distributions for the delivery times for several of the pallet weight categories.

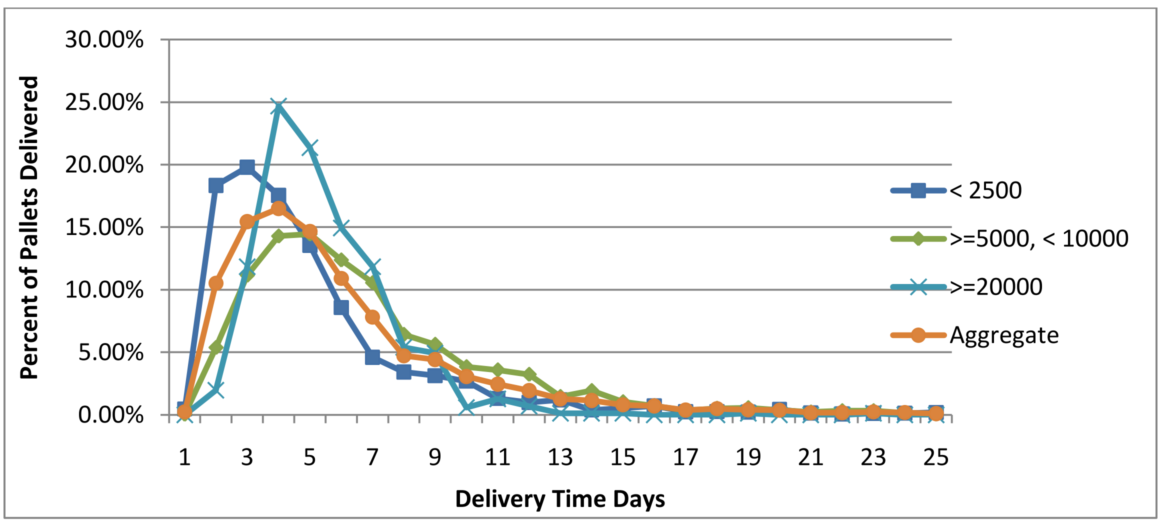


Figure 12: Distribution, Pallet Weight (pounds)

Simulation Model Analysis

Process Analyzer

The *Process Analyzer* was used to complete a 2^5 factorial designed experiment. The results of the model are shown in Table 21. Each treatment is defined by a five character combination of "+", and "-". Each designator refers to the level at which each factor is set in the design as indicated in Table 11. The colors indicate whether the response generated by each treatment was better (grey) or worse (white) than the treatment combination run using historical values or baseline (black).

Table 21: 2^5 Factorial Design Results (Day^2)

Treatment	Design	AZ1	AZ3	JAA	KBL	KDH	OA1	OA4	TOT
1	−−−−−	28.80	34.89	38.38	38.80	31.44	26.74	34.76	233.81
2	−−−−+	31.13	35.26	39.80	37.78	29.23	29.07	37.09	239.37
3	−−−+−	31.82	34.02	35.16	37.11	30.81	28.79	34.99	232.71
4	−−−++	33.35	37.73	36.90	40.17	29.89	30.58	36.04	244.67
5	−−+−−	43.96	35.63	37.52	38.61	40.59	27.04	36.73	260.08
6	−−+−+	46.43	34.58	37.48	38.84	41.74	29.87	35.94	264.87
7	−−++−	47.38	37.08	39.13	36.99	42.28	29.13	35.61	267.61
8	−−+++	51.57	38.12	34.47	37.13	43.70	29.39	38.07	272.44
9	−+−−−	35.27	39.81	44.32	43.60	33.99	33.69	42.87	273.54
10	−+−−+	44.72	39.81	44.02	40.34	35.45	35.17	43.51	283.03
11	−+−+−	38.50	45.78	52.12	42.94	36.08	34.13	43.88	293.44
12	−+−++	37.31	38.10	40.33	40.10	35.88	36.74	36.45	264.91
13	−++−−	48.12	38.84	36.93	39.49	45.44	33.99	37.63	280.44
14	−++−+	55.35	40.36	37.23	38.60	46.87	35.90	43.11	297.42
15	−+++−	59.53	40.82	57.34	41.88	50.82	39.65	35.00	325.06
16	−++++	61.75	47.88	40.56	40.92	50.63	38.74	46.43	326.92
17	+−−−−	33.40	70.37	80.24	48.84	33.71	26.74	81.53	374.82
18	+−−−+	33.26	71.25	77.65	47.81	33.24	28.71	77.94	369.86
19	+−−+−	33.52	79.59	75.87	46.37	32.55	28.49	75.14	371.54
20	+−−++	33.95	68.31	77.75	46.59	34.29	30.02	74.30	365.21
21	+−+−−	46.48	68.58	74.44	50.67	42.90	28.40	71.26	382.74
22	+−+−+	48.56	72.09	84.57	46.84	45.63	30.11	80.70	408.49
23	+−++−	51.63	72.08	69.68	42.84	45.39	29.11	74.37	385.10
24	+−+++	53.39	79.88	84.70	46.90	44.77	30.41	69.21	409.26
25	++−−−	37.66	79.82	82.37	44.14	36.91	33.89	81.23	396.02
26	++−−+	41.73	88.57	81.82	52.35	42.66	37.82	80.93	425.87
27	++−+−	50.50	77.11	81.48	45.81	50.60	36.24	80.12	421.85
28	++−++	42.54	85.13	77.43	45.27	37.69	38.19	77.31	403.57
29	+++−−	58.03	71.93	77.41	57.82	53.68	35.30	77.89	432.06
30	+++−+	57.85	78.24	83.05	49.18	54.39	36.37	78.36	437.43
31	++++−	50.50	77.11	81.48	45.81	50.60	36.24	80.12	421.85
32	+++++	60.70	85.40	76.45	49.88	52.31	38.72	77.61	441.07
33	Base	38.01	45.59	44.48	39.16	37.09	31.65	46.36	282.34
			Base Case		Better		Worse		

This table of values clearly indicates that, in general, as transload time variance is increased, the delivery time variance also increases.

Treatment 32 is the only design point with all factors set to their upper level. The total variance for this design is higher than any other treatment, and the variance at each APOD is at least 20% more than the baseline, treatment 33. Of the five designs with just one factor set at its lower value (treatments 16, 24, 28, 30 and 31), none of the responses report less variance than the baseline. The best total variance measured among this set of scenarios is scenario 16, which was still 15.8% worse than the baseline.

Treatments 17-32 differ from 1-16 because the transload time variance at *OA1* is set to its upper level for each of the treatments. The total delivery time variance for each of these treatments is above the baseline. The lowest value is treatment 20 which was 29.4% greater than the baseline. Additionally, note that of the 112 different responses for these treatments, only 18 performed better than the baseline. Furthermore, notice that of these 18 responses the majority are under the response *OA1*. Changes in the transload time at any transload hub should have no impact on the cargo delivery time variance for the same location. These results indicate that the transload time variance at *OA1* has an adverse effect on the delivery time variance in the system.

OptQuest

Scenario 1

Scenario 1 utilizes the standard deviations from the distributions for each of the five busiest transload hubs in order to minimize cargo delivery time variance. Table 22 shows the values for the best solution found via OptQuest and the values for the controls used by OptQuest to generate the best solution for each of the eight responses.

Table 22: OptQuest Results, Scenario 1

Response	Best Sol (Days^2)	Controls (Days)				
		σ_{T-ADA}	σ_{T-IUD}	σ_{T-KDH}	σ_{T-KEZ}	σ_{T-OA1}
σ^2_{TOT}	225.68	2.32	4.31	1.34	14.98	2.24
σ^2_{AZ1}	28.05	2.32	4.31	1.22	14.89	2.26
σ^2_{AZ3}	32.81	5.39	4.52	4.19	12.06	2.37
σ^2_{JAA}	31.72	3.06	4.60	1.32	15.00	2.24
σ^2_{KBL}	33.77	12.48	9.99	4.96	6.87	2.37
σ^2_{KDH}	28.02	2.55	4.31	1.22	14.90	2.24
σ^2_{OA1}	23.92	2.32	4.31	1.22	2.38	14.94
σ^2_{OA4}	30.32	2.77	7.31	1.22	11.75	2.24

The control values for six of the responses, σ^2_{TOT}, σ^2_{AZ1}, σ^2_{AZ3}, σ^2_{JAA}, σ^2_{KDH}, σ^2_{OA4}, are similar in that they shift the majority of the variation to the control σ_{T-KEZ}. This implies that the transload time at KEZ has the least effect on delivery time variance for each of these responses. The other two responses are unique because the majority of variation in transload times is shifted to different transload hubs. The delivery time variance at KBL, σ^2_{KBL}, shifts the majority of transload time variance to ADA, σ_{T-ADA}. The majority of the transload time variance for OA1, σ^2_{OA1}, is intuitively shifted to its own transload hub, σ_{T-OA1}. Since variation at its own transload hub does not affect the delivery time variance into the same hub, variation can be shifted to σ_{T-OA1} without increasing variance. Although not shown in Table 22, the delivery time variance at KDH, σ^2_{KDH}, also indicated little influence from higher values of variance at its own transload hub, σ_{T-KDH}. The sixth best solution for the response σ^2_{KDH} is 28.79 and the transload time standard deviation, σ_{T-KDH}, was set to 8.91.

Table 23 shows the changes in objective function value from the base case level to the best solution generated through OptQuest for each of the eight responses. It clearly indicates that shifting transload time variance is able to capture a positive result for each response.

Table 23: Objective Function Results, Scenario 1

Objective	**Base Lev (Days^2)**	**Best Sol (Days^2)**	**Decrease**
σ^2_{TOT}	282.34	225.68	20.07%
σ^2_{AZ1}	38.01	28.05	26.20%
σ^2_{AZ3}	45.59	32.81	28.03%
σ^2_{JAA}	44.48	31.72	28.69%
σ^2_{KBL}	39.16	33.77	13.76%
σ^2_{KDH}	37.09	28.02	24.45%
σ^2_{OA1}	31.65	23.92	24.42%
σ^2_{OA4}	46.36	30.32	34.60%

The sum of all the variances, σ^2_{TOT}, was decreased by more than 20%. The largest decrease in objective function value, 34.60%, occurred at OA4 and the smallest decrease, 13.76%, occurred at KBL. All of the responses were able to decrease objective function value by more than 10%.

Finally, Table 24 shows the best solution found via OptQuest for the objective function value total delivery time variance, σ^2_{TOT} and compares it to the base level for each of the eight different responses.

Table 24: Total Delivery Time Variance, Scenario 1

	σ^2_{TOT}	σ^2_{AZ1}	σ^2_{AZ3}	σ^2_{JAA}	σ^2_{KBL}	σ^2_{KDH}	σ^2_{OA1}	σ^2_{OA4}
Base Lev (Days^2)	282.34	38.01	45.59	44.48	39.16	37.09	31.65	46.36
OptQuest (Days^2)	225.68	31.08	33.79	35.15	35.01	31.03	27.86	31.77
Decrease	20.07%	20.06%	18.23%	25.88%	20.98%	10.60%	16.34%	11.97%

Table 24 indicates that using the total delivery time variance as the objective function value, in this case, decreases the level of variance at each of the APODs. The improvements range from 10.60% at KDH to 25.88% at JAA.

Scenario 2

Scenario 2 utilizes the mean transload times at each of the five busiest transload hubs as well as the mean port hold times at each of the six busiest pallet APOEs in order to reduce the delivery time variance at each of the seven different pallet APODs. Results for each of the eight different objective functions are described below.

Table 25 shows the best solution found via OptQuest for each objective function as well as the control values used by OptQuest to generate the best case solution. As was previously mentioned, the mean transload times of *Scenario 2* were only allowed to increase from their historical value.

Table 25: OptQuest Results, Scenario 2

Objective	Best Sol (Days^2)	Controls (Days) μ_{T-ADA}	μ_{T-IUD}	μ_{T-KDH}	μ_{T-KDH}	μ_{T-OA1}
σ^2_{TOT}	267.65	4.94	2.59	3.68	4.15	3.56
σ^2_{AZ1}	32.92	4.90	2.58	3.63	4.13	3.83
σ^2_{AZ3}	38.59	4.82	2.58	3.62	4.16	3.48
σ^2_{JAA}	42.28	6.97	2.68	3.95	4.30	3.67
σ^2_{KBL}	36.03	6.16	2.58	4.10	4.59	4.11
σ^2_{KDH}	31.10	4.94	2.60	4.60	4.25	3.74
σ^2_{OA1}	28.04	5.49	2.59	3.91	4.41	4.06
σ^2_{OA4}	41.86	6.02	2.85	4.15	4.80	4.47

	Controls μ_{O-CHS}	μ_{O-DOV}	μ_{O-IUD}	μ_{O-KEZ}	μ_{O-KWI}	μ_{O-WRI}
σ^2_{TOT}	3.52	3.60	3.03	4.11	3.63	2.74
σ^2_{AZ1}	3.52	3.66	6.04	7.79	3.64	3.05
σ^2_{AZ3}	3.83	3.51	2.97	4.00	3.62	2.75
σ^2_{JAA}	3.51	3.77	5.31	6.27	3.69	2.75
σ^2_{KBL}	3.66	4.54	3.95	5.00	3.75	3.36
σ^2_{KDH}	3.53	3.68	4.93	4.36	4.11	2.86
σ^2_{OA1}	3.63	3.91	3.31	5.25	3.71	3.34
σ^2_{OA4}	3.67	4.52	5.05	5.68	3.80	2.77

Table 26 shows the objective function results from each of the eight different objectives investigated via OptQuest. Each of the objective functions investigated by OptQuest decreased from the baseline by varying amounts which averaged just over 10% overall. The greatest decrease, 16.15%, occurred for the objective σ^2_{KDH} while the smallest decreases, approximately 5%, occurred at σ^2_{TOT} and σ^2_{JAA}.

Table 26: Objective Function Results, Scenario 2

Objective (Days^2)	Base Lev	Best Sol	Decrease
σ^2_{TOT}	282.34	267.65	5.20%
σ^2_{AZ1}	38.01	32.92	13.39%
σ^2_{AZ3}	45.59	38.59	15.35%
σ^2_{JAA}	44.48	42.28	4.95%
σ^2_{KBL}	39.16	36.03	7.99%
σ^2_{KDH}	37.09	31.10	16.15%
σ^2_{OA1}	31.65	28.04	11.41%
σ^2_{OA4}	46.36	41.86	9.71%

Table 27 displays the values for each of the eight responses reported under the total delivery time variance objective function, σ^2_{TOT}. The values of all but one of the responses show a decrease in variance. These results indicate that the delivery time variance at all but one of the APs can be decreased by using the configuration of settings shown in Table 25, under objective σ^2_{TOT}. The APs of KDH, OA1 and OA4 all experience a decrease in delivery time variance greater than 5% of the historical value while AZ1, AZ3, and KBL all experience a smaller decrease. Finally, JAA experiences an increase in delivery time variance of 2.31%

Table 27: Total Delivery Time Variance, Scenario 2

	σ^2_{TOT}	σ^2_{AZ1}	σ^2_{AZ3}	σ^2_{JAA}	σ^2_{KBL}	σ^2_{KDH}	σ^2_{OA1}	σ^2_{OA4}
Base Lev (Days^2)	282.34	38.01	45.59	44.48	39.16	37.09	31.65	46.36
OptQuest (Days^2)	267.65	36.88	44.67	45.51	37.21	33.07	29.49	40.81
Decrease	5.20%	2.96%	2.01%	-2.31%	4.97%	10.83%	6.82%	11.96%

One of the drawbacks to Scenario 2 is that the delivery time mean inevitably increases as transload time means increase.

Scenario 3

Scenario 3 utilizes the controls described in *Scenario 1* along with the port hold times at each of the six busiest pallet APOEs in order to reduce delivery time variance. Table 28 shows the results from the best solution for each of the eight objective functions used in OptQuest. It also shows the values for each of the 11 controls that resulted in the best objective function value.

Table 28: OptQuest Results, Scenario 3

		Controls (Days)				
Response	**Best Sol (Days^2)**	$\boldsymbol{\sigma_{T-ADA}}$	$\boldsymbol{\sigma_{T-IUD}}$	$\boldsymbol{\sigma_{T-KDH}}$	$\boldsymbol{\sigma_{T-KEZ}}$	$\boldsymbol{\sigma_{T-OA1}}$
σ_{TOT}^2	223.69	2.32	4.31	1.32	15.00	2.24
σ_{AZ1}^2	24.03	2.36	4.31	1.55	15.00	9.02
σ_{AZ3}^2	30.27	11.21	5.46	12.34	3.33	2.46
σ_{JAA}^2	27.76	9.77	4.34	13.34	4.46	2.24
σ_{KBL}^2	28.83	14.59	4.31	15.00	2.38	2.24
σ_{KDH}^2	24.62	2.37	4.31	11.30	6.10	9.02
σ_{OA1}^2	19.96	2.32	4.31	4.08	10.34	15.00
σ_{OA4}^2	28.28	10.68	4.83	12.44	3.66	2.24

	Controls					
	$\boldsymbol{\sigma_{O-CHS}}$	$\boldsymbol{\sigma_{O-DOV}}$	$\boldsymbol{\sigma_{O-IUD}}$	$\boldsymbol{\sigma_{O-KEZ}}$	$\boldsymbol{\sigma_{O-KWI}}$	$\boldsymbol{\sigma_{O-WRI}}$
σ_{TOT}^2	3.73	3.44	3.59	4.00	3.81	2.72
σ_{AZ1}^2	3.24	1.74	1.71	2.30	3.62	1.56
σ_{AZ3}^2	2.12	2.12	2.35	2.54	2.14	1.86
σ_{JAA}^2	1.94	1.75	2.54	2.14	3.16	1.37
σ_{KBL}^2	1.87	1.66	1.71	2.01	1.91	1.37
σ_{KDH}^2	2.26	2.39	2.17	2.54	2.84	1.49
σ_{OA1}^2	1.87	1.66	1.71	2.01	1.91	1.37
σ_{OA4}^2	2.12	1.94	2.82	2.29	2.27	1.59

The results for the transload time standard deviations differ from those from *Scenario 1*. In *Scenario 1,* six of the eight objective functions that were run loaded a majority of variation on the KEZ transload hub. In *Scenario 3,* this differs because the majority of variation is loaded on the KDH transload hub in five of the eight objective functions that were run.

Table 28 also shows that the controls for the six port hold time standard deviations for the total delivery time variance objective function, σ_{TOT}^2, were each set at or near their suggested or historical values shown in Table 16. The results for the other seven objective function values were consistently less than there suggested values. This indicates that in order to uniformly reduce the variance at each of the APODs the transload hubs are most significant. The results from *Scenario 1* are almost identical to those of *Scenario 3*. However, for the other seven objective functions that minimize the amount of variance at an individual APOD, the port hold times at each APOE are important and result in decreased objective function values.

Table 29: Objective Function Results, Scenario 3

Objective (Days^2)	Base Lev	Best Sol	Decrease
σ_{TOT}^2	282.34	223.69	20.77%
σ_{AZ1}^2	38.01	24.03	36.78%
σ_{AZ3}^2	45.59	30.27	33.60%
σ_{JAA}^2	44.48	27.76	37.59%
σ_{KBL}^2	39.16	28.83	26.38%
σ_{KDH}^2	37.09	24.62	33.62%
σ_{OA1}^2	31.65	19.96	36.94%
σ_{OA4}^2	46.36	28.28	39.00%

The results shown in Table 29 indicate that this method of variance reallocation throughout the system is capable of generating at least a 20% increase in variance reduction for each of the different objective functions. As shown, the smallest decrease in objective function value is for the total delivery time variance at 20.77%. The remainder of the objective functions reduced through OptQuest range from a 26.38% decrease to a 39.00% decrease.

Further analysis demonstrates that reducing the variance at an individual port does not necessarily result in overall variance reduction. Table 30 shows the response for the total delivery time variance for each of the eight different objective functions used. Only half surpass the base case standard of 282.34. The other half show significant increases in total delivery time variance despite local minimizations of delivery time variance at an individual APOD.

Table 30: Total Delivery Time Variance for Each Objective Function

	σ^2_{TOT}	σ^2_{AZ1}	σ^2_{AZ3}	σ^2_{JAA}	σ^2_{KBL}	σ^2_{KDH}	σ^2_{OA1}	σ^2_{OA4}
σ^2_{TOT} (Days^2)	223.69	355.60	289.63	244.05	267.22	338.43	411.71	253.47

The results for the reduction of total delivery time variance for *Scenario 3*, like *Scenario 1*, show reductions in variance at all APOD. Reductions in variance at each individual APOD are shown in Table 31. They range from an 8.43% decrease at OA1 to a 37.72% decrease in delivery time variance at OA4.

Table 31: Total Delivery Time Variance, Scenario 3

	σ^2_{TOT}	σ^2_{AZ1}	σ^2_{AZ3}	σ^2_{JAA}	σ^2_{KBL}	σ^2_{KDH}	σ^2_{OA1}	σ^2_{OA4}
Baseline (Days^2)	282.34	38.01	45.59	44.48	39.16	37.09	31.65	46.36
OptQuest (Days^2)	223.69	33.82	30.34	35.88	35.57	30.23	28.98	28.87
Decrease	20.77%	11.03%	33.45%	19.35%	9.16%	18.49%	8.43%	37.72%

This indicates that reallocation of variance at transload hubs and APOE can result in reductions in delivery time variance at all ports.

Scenario 4

Scenario 4 is a combination of *Scenario 2* and *3*. It combines the controls from both scenarios in order to reduce the total delivery time variance in the system. A single objective function, σ^2_{TOT}, was investigated with this scenario because of the significant amount of controls that were utilized. *Scenario 4* also achieved positive decreases in delivery time variance at each pallet APOD as shown in Table 32. The total delivery time variance from this scenario improves just 2.31% compared to the best objective function value from *Scenario 3*.

Table 32: Total Delivery Time Variance, Scenario 4

	σ^2_{TOT}	σ^2_{AZ1}	σ^2_{AZ3}	σ^2_{JAA}	σ^2_{KBL}	σ^2_{KDH}	σ^2_{OA1}	σ^2_{OA4}
Baseline (Days^2)	282.34	38.01	45.59	44.48	39.16	37.09	31.65	46.36
OptQuest (Days^2)	217.19	34.42	32.37	31.51	35.36	25.03	26.51	31.98
Decrease	23.08%	9.44%	29.00%	29.16%	9.71%	32.51%	16.23%	31.02%

Summary

The results from Chapter IV show that delivery time variance reduction is possible through reallocation of variance at transload hubs. Results from the designed experiment, *Scenario 1*, *Scenario 3* and *Scenario 4* indicate that delivery time variance can be best reduced by concentrating efforts on reducing transload time variance at OA1. Transload time variance reductions at the other transload hubs also reduces delivery time variance but to a lesser extent. OptQuest was able to improve total delivery time variance by more than 20% and also achieved significant improvements for delivery time variance at each individual pallet APOD. The subsequent chapter summarizes the conclusions drawn from this research, outlines the obstacles to implementation of results and suggests future areas of research that broaden the scope of this research effort.

V. Conclusion

The military cargo delivery system enables successful military operations. This research effort outlines the aerial component of this system and many of the different methods used previously to improve it. While focusing on delivery time variance reduction, a simulation model was developed that models cargo movement from various APOEs throughout the world into Afghanistan, a key area of immediate interest in current and future military operations. The GATES database provided a wealth of data for this research effort. This data provided insights into delivery time variance and enabled proper modeling of the system and validation of the simulation. Finally, the model was manipulated through OptQuest and other software tools in order to determine improvements in configurations that could lead to a more efficient system and delivery time variance reductions.

Conclusions

This analysis showed that proper reallocation of variance across different transload hubs and APs can decrease delivery time variance for the system as a whole and for each of the pallet APODs. Several additional issues must be addressed before implementation of policy can be considered.

First, the theory must be brought to practice. Some method or practice must be devised to allow the solutions outlined in this research to be implemented. This could be the most challenging issue. Although reallocation of variance may not seem practical, this research effort identifies areas where additional resources could be placed and special measures implemented to increase the performance of the cargo delivery system.

Second, the cost of implementation of these results must be weighed against the potential benefit. The cost includes, but is not limited to, policy changes that require the reallocation of and purchase of additional assets to implement changes. New standards must be created, and personnel need to adapt to new policies and requirements. The benefit of these changes is a more reliable system with less delivery time variance that ensures more on-time deliveries of needed supplies and equipment to military forces. It must be determined if these potential improvements in delivery time variance are worth the time, effort and resources that must be expended to achieve them. This method should also be compared to other methods to determine if a more efficient way of achieving the same results exists.

Third, the feasibility of asset reallocation must be considered. A question which must be answered is: Is it even possible to reallocate resources in such a way that variance in transload times can be reduced? It might be more likely that new measures could be enacted to allow better monitoring of cargo en route leading to reductions in delivery time variance.

Finally, a timeline of implementation should be considered. In an ever changing political and economic environment, it is unlikely that the current schedule of military operations remains unchanged. The location, tempo and type of military operations can rapidly change and quickly render costly implementation of policies useless. Focusing efforts on improving cargo delivery time variance for cargo moving into Afghanistan is presently of benefit but could change suddenly.

Recommendations for Future Research

Several areas of future research have been revealed through the process of this research. First, studies could be conducted to determine feasibility of implementation of programs to support the results of this research as mentioned in the previous paragraphs. The simulation could also be improved by incorporating available resources at APs and service times gleaned from experienced personnel instead of relying on data distributions of transload times and port hold times.

Appendix A: Blue Dart

The Value of Delivery Time Variance Reduction

The military's need for a rapid, agile and efficient distribution system grows daily. Efforts are continually undertaken to increase efficiency and performance of the system. Many efforts focus on reducing the amount of time it takes to deliver goods or increasing the delivery capacity of the system. One important area that is often overlooked is increasing the amount of on-time deliveries or reducing variation in delivery times. Reducing variation in delivery times will lead to a more efficient system and more satisfied customers.

Large variance in delivery times causes products and cargo to be ordered more often and earlier than necessary. For example if you needed a product to be delivered by a certain date and knew the delivery could take five to ten days, you would need to order it at least ten days in advance to ensure its availability. However, if you knew the product would be delivered in exactly seven days, you would only order it seven days in advance.

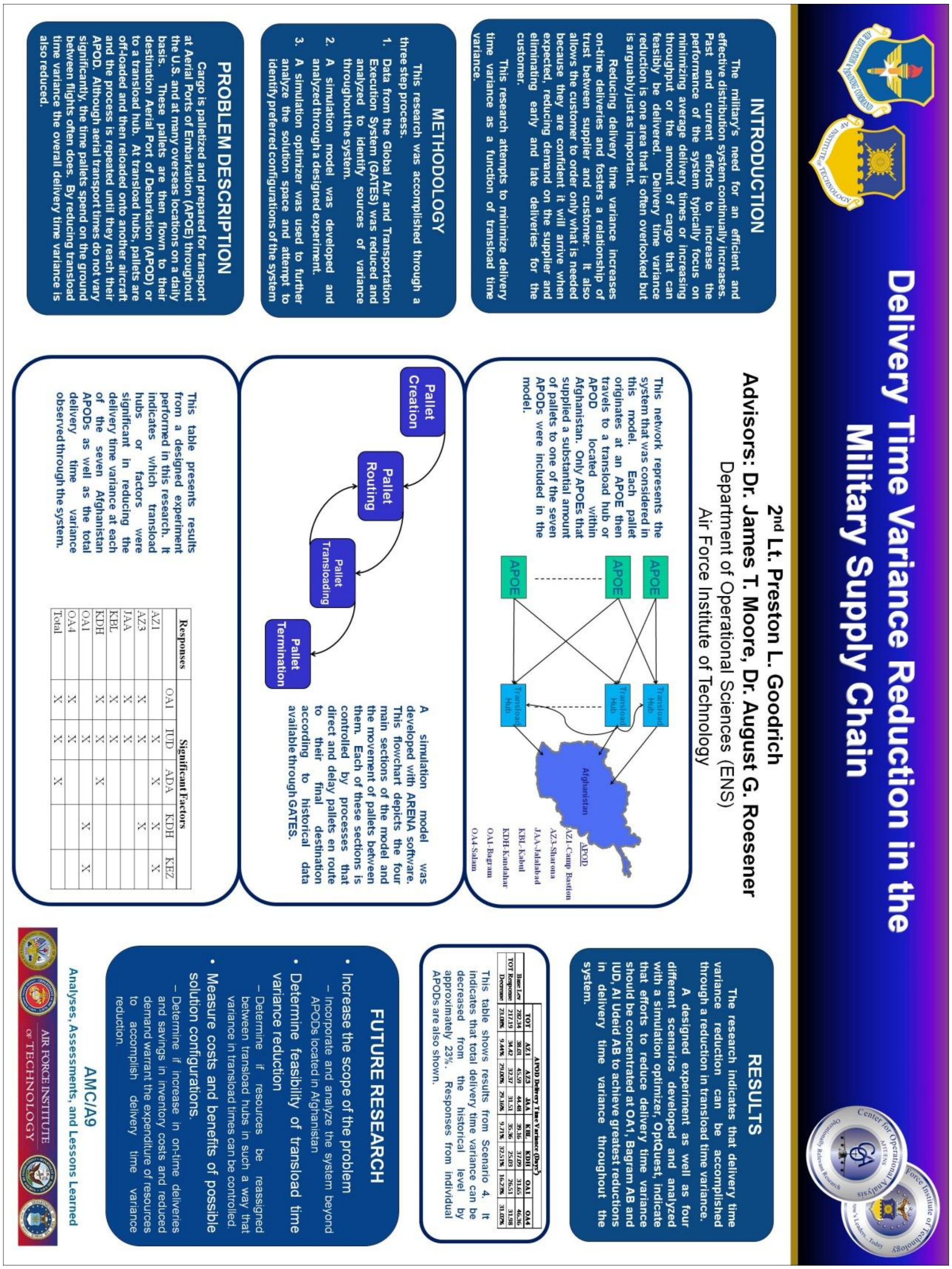
The more reliable delivery has many advantages. First, the customer does not order the product before it is necessary, reducing demand on the provider. Second, the customer does not receive the product before needed, preventing the need for storage. In many situations the customer could prefer an on-time delivery even if the average delivery time is increased.

Over the past decade the ability to track packages and determine when they will arrive has increased significantly in the military and commercial sectors. Many of us are now familiar with purchasing items through a website. A delivery tracking ability is now commonly provided with many of these purchases. Tracking allows the customer to determine where there products are located and predict more accurately when they will arrive. This allows the customers to plan accordingly and increases satisfaction. Similar systems provide cargo tracking information and data in the military. The growing amounts of data provide insight to delivery time variance in the military supply chain. These insights can be leveraged to provide a more effective delivery of cargo.

Aerial deliveries in the military must often be off loaded from aircraft and reloaded onto other aircraft at transload hubs. The completion time of this operation is in some cases highly variable which causes delivery time variance to be increased. Reduction of variance in completion times at these transload hubs leads to decreases in delivery time variance. This is important because it provides a more reliable delivery for customers in the military supply chain.

Reliable delivery of cargo in the military supply chain is of great benefit for the troops in the field that are responsible for carrying out the day to day operations of our military in austere locations. By focusing on decreasing variance in delivery times of cargo the supply chain will become less congested and customers will be more satisfied by on-time deliveries. Emphasis in reducing variance at transload hubs and other areas throughout the supply chain will greatly impact the performance of the military supply chain.

Appendix B: Summary Chart



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Vita

Second Lieutenant Preston L. Goodrich graduated from Burley High School in Burley, Idaho in 2002. He entered undergraduate studies at the United States Air Force Academy in Colorado Springs, Colorado where he graduated with a Bachelor of Science degree in Economics in May 2008 and received his commission as an Air Force Officer. In August 2008, he entered the Graduate School of Engineering and Management, Air Force Institute of Technology. Upon graduation, he will be assigned to the HQ USAF/A1.

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14. ABSTRACT

USTRANSCOM is currently responsible for the daily shipment of supplies to forward operating bases throughout Afghanistan. Aerial cargo shipments are an important method used to quickly deliver items that are needed immediately. Currently delivery times vary greatly. This variation causes confidence in on-time deliveries to decrease. As a result shipments are demanded early and often, causing bottlenecks in the transportation system and fewer on-time deliveries. This paper analyzes data gathered through the global transportation network to determine shipment characteristics that cause the greatest amount of delivery time variance. A simulation is developed using ARENA that models cargo shipments into aerial ports in Afghanistan. Design experiments and a simulation optimizer, OptQuest, are used to determine most effective methods of reducing delivery time variance at individual aerial ports in Afghanistan as well as the system as a whole. The results indicate that adjustments in port hold times can decrease the overall delivery time variance in the system.

15. SUBJECT TERMS

Military Supply Chain, Delivery Time Variance, Variance Reduction, Simulation, ARENA, OptQuest

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